



Insights into MIMO-OFDM Channel Modeling and Estimation Techniques for Enhanced 5G Wireless Communication Systems: A Review

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ABSTRACT:

To enhance spectrum utilization, energy efficiency, and quality of service (QoS) concerning factors such as latency, reliability, and security, the implementation of 5G systems is recommended. These systems are designed to handle significant volumes of mobile data traffic and a diverse array of communication connections. Massive multiple-input and multiple-output (mMIMO) is a crucial wireless communication technique within 5G networks. It offers improved spectrum efficiency and connection reliability, serving numerous users with a focus on efficiency and precision. The wireless communication channel often affects transmitted signals due to its inherent physical characteristics, causing attenuation, distortion, delays, and phase shifts in the signals received by the communication system's receiver. Therefore, delivering precise and current channel estimates is essential to counteract these effects. This accuracy is crucial for signal demodulation, equalization, decoding, and various other baseband processing tasks at the receiver end. This article provides an extensive examination of MIMO channel models and channel estimation methods in 5G wireless communication systems. We begin with a concise overview of OFDM and MIMO-OFDM systems, followed by an outline of the overarching MIMO channel model and a detailed description of three primary MIMO channel models: physical, analytical, and standardized. Lastly, we classify the techniques for channel estimation.

Keywords: OFDM, MIMO-OFDM, Channel models, Channel estimation techniques, Wireless channel.

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1. INTRODUCTION

We are amidst a wireless technology revolution, spurred by society's appetite for novel offerings such as smart cities, autonomous vehicles, augmented reality, and beyond. These

sophisticated services necessitate a substantial escalation in data speeds, potentially soaring to levels 1000 times greater, alongside real-time applications that must meet stringent latency requirements. At this moment, wireless



communication stands as one of the liveliest sectors in technology communication systems. It earns its name wireless due to its utilization of wireless pathways instead of wired ones. This swift expansion has been intricately linked with the technological progress of our era. Wireless communication has facilitated a plethora of services, spanning from voice to data and extending further. The technology has been categorized based on its generations, delineating transfer rates and service types. These generations are denoted as 1G, 2G, 3G, 4G, 5G, and 6G.

The adverse impacts on signals transmitted through a wireless communication channel stem from the inherent physical characteristics of the channel. The transmitted signal undergoes intricate interactions with the environment. These interactions encompass reflections caused by sizable objects, diffraction of electromagnetic waves around obstacles, and signal scattering. The cumulative outcomes of these interactions manifest as numerous signal replicas, known as multipath signals, exhibiting various degrees of attenuation, distortion, delays, and phase shifts upon reaching the receiver. These multipath signals may either reinforce or negate one another. When destructive interference prevails, the signal strength can significantly diminish, a phenomenon commonly referred to as fading. In cases of pronounced destructive interference, the channel experiences what is known as a deep fade. This can lead to a transient communication breakdown due to a drastic decline in the channel's signal-to-noise ratio (SNR). Wireless

communication channels are characterized by two types of fading effects: large-scale fading and small-scale fading[3]. Large-scale fading pertains to the average attenuation of signal power or path loss observed over extensive distances due to mobility across large areas. Small-scale fading results from significant fluctuations in both the amplitude and phase of the transmitted signal, primarily influenced by minor changes in spatial separation between a transmitter and receiver. When numerous reflective paths are present without a direct line-of-sight signal component, this phenomenon is known as Rayleigh fading, characterized by the Rayleigh probability density function (pdf) describing the received signal envelope. Conversely, if a dominant non-fading signal component, such as a line-of-sight propagation path, exists, the envelope of such small-scale fading is depicted by a Rician pdf. Another characteristic of wireless communication channels is the Doppler shift, which arises due to the relative movement between the transmitter and receiver, as well as any other objects within the channel. Consequently, this introduces a time-varying aspect to the wireless channel[4]. Figure 1 illustrates a typical wireless communication channel experiencing multipath effects. Due to various environmental pathways, each multipath signal received at the base station from mobile transmitters, local scatterers, and the remote primary reflector exhibits variations in amplitude, carrier phase shift, time delay, and Doppler shift. If the transmitters are in motion, these parameters of the multipath signals will also fluctuate over time.

4435

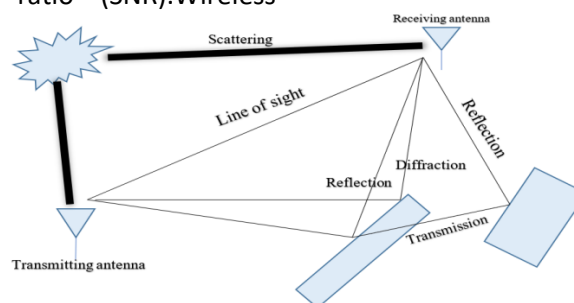


Figure 1: Multi-path Propagation within the Wireless Communication Medium[108]

In wireless systems, devices can be either mobile or fixed. When devices are mobile, both the transmitting and receiving devices are in motion, causing the channel to dynamically change over time, resulting in a time-varying channel. For fixed

devices, multiple antennas are typically mounted. As data is transmitted from the transmitting antenna to the receiving antenna through the wireless channel, the signal may traverse various paths, leading to signal degradation due to

multipath propagation. Consequently, recovering the attenuated signal at the receiver becomes challenging, making accurate channel estimation crucial in wireless communication systems.

Channel estimation involves acquiring the Channel State Information (CSI), which is essential for understanding the characteristics, behaviour, and reliability of the channel. One of the primary hurdles to achieving peak performance in wireless communication systems is obtaining precise CSI at the receiving end to enable coherent detection of the transmitted signal. Without CSI at the receiver, demodulating and detecting the transmitted signal can only be done through non-coherent means, such as differential demodulation. However, non-coherent detection results in a reduction of about 3-4 dB in signal-to-noise ratio (SNR) compared to coherent detection[5]. To mitigate this significant loss, research has focused on advancing channel estimation techniques to provide CSI at the receiver, facilitating coherent detection of transmitted data in wireless communication systems.

CSI acquisition can be achieved through various channel estimation algorithms. This estimation process occurs at the receiver, using a predefined set of symbols or sequences known as pilot symbols, which are assumed at the transmitter. Channel estimation methods determine the channel impulse response for each transmitted known symbol or burst, along with their corresponding received samples. Technologies like OFDM and MIMO-OFDM enable the transmission of these data bursts or symbols at high rates wirelessly through the channel.

1.1 Features of Channel Estimation

Channel estimation is commonly conducted by transmitting a pilot signal from the transmitter and measuring its reception at the receiver.

- ✓ An ample quantity of pilot signals must be transmitted for the receiver to attain a sufficiently accurate estimation of the channel's response.
- ✓ In the downlink of a wireless communication system, multiple

terminals can utilize a single pilot transmission from an access point (or base station) to estimate the unique characteristics of the downlink channels extending from the access point to each terminal.

- ✓ In the uplink, each terminal must independently transmit a pilot signal to allow the access point to estimate the uplink channel extending from the terminal to the access point.
- ✓ In an OFDM system, the N sub-bands might encounter varying effective channels, influenced by diverse fading and multipath effects, leading to distinct complex channel gains for each sub-band.

A vast array of machine-type devices will join the Internet of Things (IoT), transmitting sensor data in real-time. The 3rd Generation Partnership Project (3GPP) outlines these needs in three categories: massive machine-type communications (mMTC), enhanced mobile broadband (eMBB), and ultra-reliable low-latency communications (URLLC). To accommodate these demands, 3GPP has updated LTE, the 4G network[6]. Additionally, Narrowband-IoT (NB-IoT) is suggested to merge MTC into LTE, positioning the narrowband signal at either the center or periphery of the band. The upcoming 5G network promises to deliver high-performance services across the board. Initially, the 3GPP has introduced New Radio (NR), primarily catering to enhanced mobile broadband (eMBB) services[7]. Key enabling technologies for meeting these diverse demands include innovative waveform design, massive multiple-input multiple-output (MIMO), and millimeter waves (mmWave). Presently, OFDM is the chosen waveform for the initial NR release, offering advantages like resilience to multipath fading and straightforward implementation[8]. However, it also has drawbacks, such as a high peak-to-average power ratio (PAPR) and prominent side lobes in the frequency domain. To address these issues, various new waveforms have been proposed for 5G, including FBMC-OQAM, GFDM, UFMC, f-OFDM, and PA-OFDM, all aiming to mitigate out-of-band emissions (OBE). Wireless OFDM systems require tracking the fading radio

4436



channel and employing multi-amplitude signaling. The combined impact of oscillator phase noise and channel estimation errors on OFDM performance in Rayleigh fading channels is examined, along with the distribution of intercarrier interference (ICI).

For small to medium bandwidth communications in OFDM and CDMA systems, channels exhibit individual sparsity while sharing a common support set. By leveraging finite rate of innovation (FRI) principles, a parametric sparse estimation technique is discussed, which is particularly relevant to MIMO communications for robust estimation and concise channel description. Lower bounds of estimation are derived considering additive white Gaussian noise[12-14]. MIMO, a widely recognized technique utilizing multiple antennas for signal transmission or reception, offers multiplexing and diversity gains. Increased antenna numbers enhance overall link capacity and performance. Massive MIMO, reducing complexity significantly by approximating sub-optimal precoding/post-coding techniques to optimal performance, is a proposed solution for 5G[9-10]. The first frequency band, operating below 6GHz, aims to achieve widespread coverage across urban, suburban, and rural areas, supporting massive MTC and transportation services. The second band, above 6GHz, known as mmWave, facilitates ultra-high broadband services. However, transmission in this band faces challenges like increased path loss and susceptibility to blockage. Hence, MIMO techniques are essential to enhance coverage[11]. In FDD systems, utilizing massive multiple input multiple outputs, a simplified Kalman filter is proposed for channel estimation based on non-orthogonal pilots. By employing a fixed grid of beams, the system induces channel sparsity for each user, enabling estimation of relevant channels using unique pilot codes per beam. In MIMO-OFDM communications, while the communication range or channel intensity is high, the predictability of Kalman Filter accuracy is uncertain. To address this, an Enhanced Kalman Filter (EKF) is introduced. Integrating the advantages of the Kalman Filter, the EKF ensures consistent accuracy and enhanced Quality of Service (QoS) for large-range wireless

communications in MIMO-OFDM environments[15-16].

2.OFDM AND MIMO-OFDM SYSTEMS

In contemporary technology, OFDM and MIMO-OFDM systems are prevalent, offering high-speed data transfer, improved quality, and optimized spectral utilization. These systems effectively mitigate interference and fading effects. This section provides a concise overview of OFDM and MIMO-OFDM systems, accompanied by basic block diagrams to aid comprehension [17].

2.1 Overview of OFDM System

OFDM, a widely used wireless technology, employs orthogonal subcarriers to transmit data symbols. These symbols, allocated across different frequencies, are densely packed without interference, conserving bandwidth. Multi-Carrier Modulation partitions high-rate data into parallel bit streams, each modulated by orthogonal subcarriers. Efficient system performance relies on the Inverse Fast Fourier Transform (IFFT) and Fast Fourier Transform (FFT) for modulation and demodulation, respectively, converting signals between frequency and time domains. Guard bands and cyclic prefixes are added to modulated signals to mitigate Inter-Symbol Interference (ISI) and Inter-Channel Interference (ICI), while pilot symbols assist in channel estimation at the receiver. Despite potential delays or noise in transmission, accurate channel estimation remains crucial for effective signal retrieval at the receiver.

OFDM systems exhibit resilience against ISI, ICI, and fading, with errors mitigated through error-detection mechanisms or diversity techniques. Integration with MIMO systems enhances performance further. Orthogonal subcarriers in OFDM prevent interference between channels, obviating the need for guard bands and simplifying transmitter and receiver design. Unlike conventional FDM, separate filters for each subchannel are unnecessary, leading to high spectral efficiency. Accurate frequency synchronization between transmitter and receiver is essential in OFDM, facilitating parallel transmission of numerous low-rate data streams instead of a single high-rate stream. Guard



intervals between OFDM symbols eliminate inter-symbol interference, rendering pulse-shaping filters unnecessary.

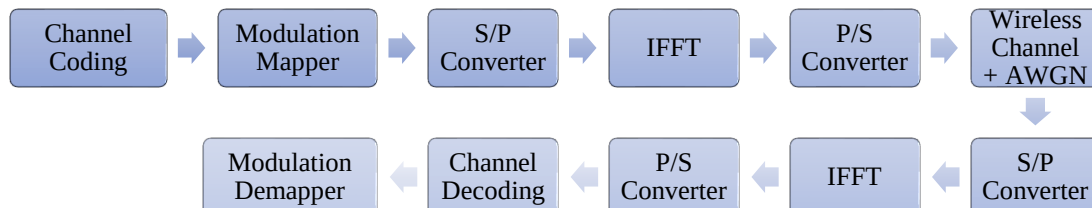


Figure 2: Block Diagram of OFDM System [20]

2.2 Overview of the MIMO-OFDM System

MIMO technology employs multiple transmitting and receiving antennas, utilizing spatial multiplexing and diversity techniques to optimize antenna configuration and channel understanding. This enhances system capacity and coverage area. Combining OFDM and MIMO into MIMO-OFDM yields superior performance, enhancing link reliability and spectrum efficiency. Signal gain increases with reception from multiple antennas, mitigating multi-path fading effects by accurately assessing channel properties through Channel State Information (CSI) evaluation.

Spatial multiplexing relies on MIMO antenna configurations, dividing a high-rate signal into several low-rate data streams transmitted through different antennas at the same frequency. When received with distinct spatial signatures at the antenna array, the receiver can

effectively separate these streams into parallel channels, boosting channel capacity and enhancing Signal-to-Noise Ratio (SNR). Diversity coding, used in the absence of transmitter channel knowledge, employs space-time coding to transmit a single data stream with full or near-orthogonal coding from each antenna. This technique leverages independent fading across multiple antenna links to improve signal diversity. Spatial multiplexing can be combined with precoding when the transmitter has channel knowledge, or with diversity coding when prioritizing decoding reliability. While spatial multiplexing techniques increase receiver complexity, they are often paired with orthogonal frequency-division multiplexing (OFDM) or Orthogonal Frequency Division Multiple Access (OFDMA) modulations to effectively address multi-path channel challenges

4438

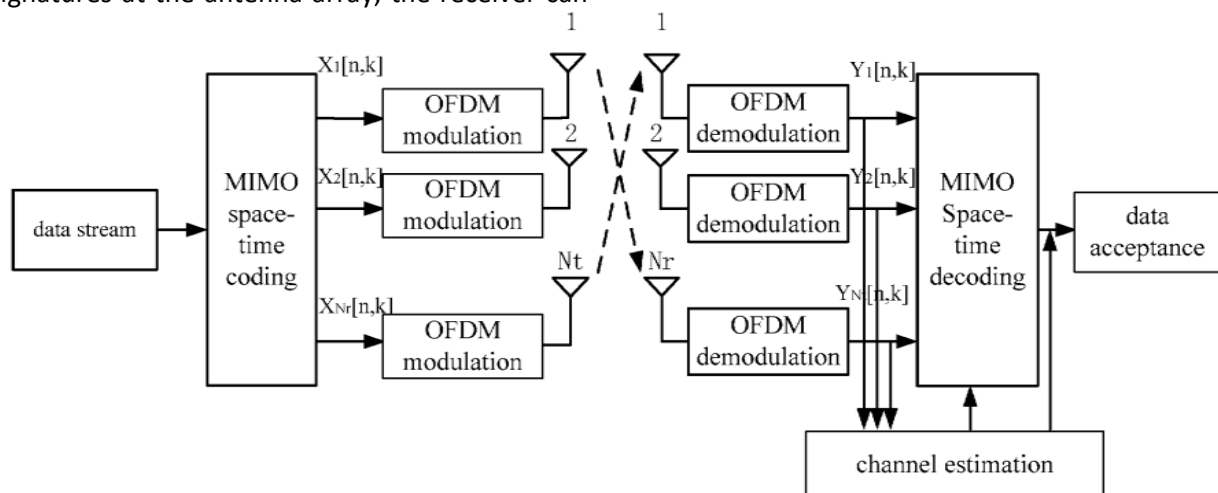


Figure 3: Block Diagram of the MIMO-OFDM System [21]

2.3 Overview of The Massive MIMO System

MIMO, a widely adopted radio technique integrated into various wireless standards like



OFDM, significantly enhances radio link capacity and reliability. In a multiuser scenario, base stations (BS) with multiple antennas serve single-antenna user equipments (UEs), sharing multiplexing gain among them. Precoding/post-coding matrices are computed to mitigate noise, multi-user interference, and hardware and channel effects, ensuring optimal MIMO benefits. Channel estimation complexity increases linearly with the number of antennas required for matrix

computation. Random matrix theory demonstrates that with a large number of antennas, small-scale fading, interference, and noise effects can be effectively suppressed, favouring linear detection schemes like maximum ratio combining (MRC) for optimal performance[18-19]. However, in scenarios with fewer antennas, equalizers based on zero-forcing or MMSE criteria are employed, albeit requiring complex matrix inversions that increase link delay.

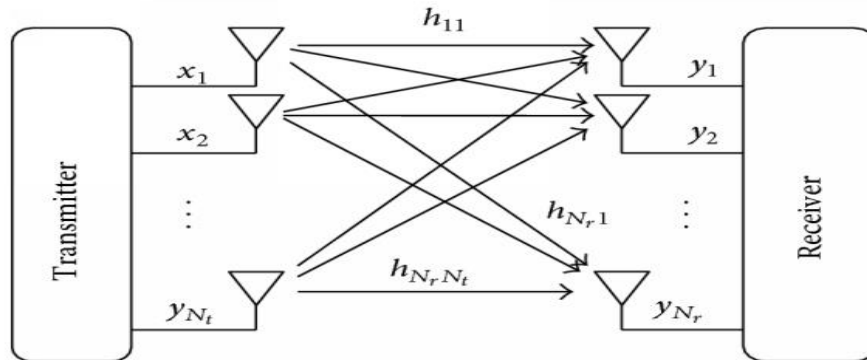


Figure 4: Diagram of Massive MIMO System [22]

3. MIMO CHANNEL MODELS

In this section, we explore the fundamental MIMO channel model and its prerequisites, along with the classification of MIMO technology. We then introduce the generalized MIMO channel model and its associated modeling techniques. The discussion proceeds to classify MIMO channel models into point-to-point, multi-user MIMO, and massive MIMO. Additionally, we provide concise descriptions of multi-user MIMO scenarios for both uplink and downlink transmissions.

3.1 The Basic MIMO Channel Model

The traditional single-antenna communication system lacks the spatial versatility offered by

multiple antennas, making the presence of multiple antennas in MIMO systems highly advantageous. These antennas provide essential spatial degrees of freedom, enabling capacity enhancement and system coverage expansion by efficiently scheduling multiple users to share the spatial channel simultaneously. The figure above illustrates how the MIMO channel conveys vital information regarding transmitting and receiving antennas. In an $n \times m$ MIMO system, where m and n denote the number of transmitting and receiving antennas respectively, the linear time-variant MIMO channel can be accurately modeled using an $n \times m$ channel matrix[24].

$$H(t, \tau) = \begin{bmatrix} h_{11}(t, \tau) & h_{12}(t, \tau) & h_{13}(t, \tau) & \dots & h_{1m}(t, \tau) \\ h_{21}(t, \tau) & h_{22}(t, \tau) & h_{23}(t, \tau) & \dots & h_{2m}(t, \tau) \\ \dots & \dots & \dots & \dots & \dots \\ h_{n1}(t, \tau) & h_{n2}(t, \tau) & h_{n3}(t, \tau) & \dots & h_{nm}(t, \tau) \end{bmatrix} \dots (1)$$

Where $h_{nm}(t, \tau)$ is the time-variant channel impulse response between the m^{th} transmit antenna and the n^{th} receive antenna.

The channel matrix in 1 encompasses antenna-type effects, configuration, frequency filtering, and orientation, enabling the formulation of comprehensive multiple input-output relationships between the length m transmit signal vector $s(t)$ and the length n receive signal vector $y(t)$, as presented in 2.

$$y(t) = H(t, \tau) s(t - \tau) + n(t) \dots (2)$$

In this context, $n(t)$ represents the accompanying noise and interference. In a time-invariant channel, the dependency of the channel matrix on t reduces to zero. Hence, $H(\tau) = H(t, \tau)$. In cases where the channel exhibits flat frequency characteristics, implying a single tap denoted by H , the equation simplifies to:

$$y(t) = Hs(t) + n(t) \dots\dots(3)$$

3.4 Classification of MIMO Technology

MIMO technology classification includes point-to-point, multiuser, and massive MIMO. These classifications are outlined briefly below.

3.4.1 Point-To-Point

In all the three MIMO technologies, point-to-point MIMO is the simplest[25,39]. Base stations (BS) equipped with antenna arrays communicate with other terminals also equipped with antenna arrays. Time and frequency division multiplexing is employed in an orthogonal manner to multiplex various terminals. However, the usefulness of point-to-point MIMO with a massive array of linked terminals can be limited by three key factors. Advanced digital signal processing techniques are used to separate data streams. The propagation environment must support independent streams between base stations and terminal antennas, which can be challenging to achieve in real-world scenarios, especially with compact arrays. Consequently, spectral efficiency scales slowly, especially near the cell edge where many terminals are situated, and where the Signal-to-Noise Ratio (SNR) is typically low due to severe path loss in propagation paths [26-27].

3.4.2 Multiuser MIMO (MU-MIMO)

In this MIMO variant, an antenna serves multiple User Equipments (UEs) using the same frequency resources [28]. Unlike point-to-point MIMO, MU-MIMO can accommodate single-antenna terminals and is less susceptible to dynamic propagation environments. However, practical implementation faces two main challenges. Both the base station and terminals require accurate Channel State Information (CSI) on the downlink, necessitating substantial resources for efficient pilot transmission in both directions, thus making it costly[29-30]. Additionally, advanced signal processing is crucial for achieving high spectral efficiency, making the system more suitable for mobile devices with lower complexity and fewer reception antennas. A comprehensive introduction to MU-MIMO downlink is provided in[31-32], detailing two algorithms employing signal processing techniques like transmitter beamforming and dirty paper coding to mitigate signal interference from other users in simple terms.

4440

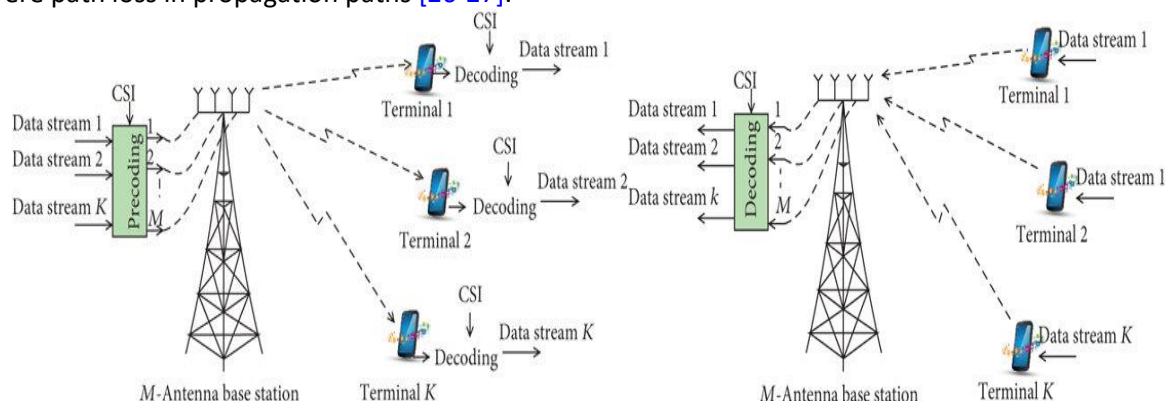


Figure5: Illustration of Multiuser MIMO Technology: (i) Downlink (ii) Uplink [23]

3.4.3 Massive MIMO

A highly practical and scalable iteration of multiuser MIMO is termed massive MIMO (mMIMO)[33]. It diverges from MU-MIMO in three key aspects. Firstly, only the Base Station

(BS) needs to possess knowledge about the channel state information in massive MIMO setups. Secondly, the number of base stations generally outweighs the number of terminal antennas. Lastly, there's a relaxed demand for



complex signal processing techniques, as straightforward linear signal processing suffices for both uplink and downlink, as noted in various studies[34-36].

3.5 MIMO Channel Modeling

The best candidates for comparing various coding, modulation, and transmission systems are accurate models of the MIMO channel. Most of the time, these models need to be thorough enough to include the most important aspects of the wireless channel. Balancing accuracy and simplicity in wireless channel modeling is consistently challenging. Two primary approaches have emerged: physical models and stochastic models. Physical models aim to replicate real-world radio channel parameters such as Direction

of Arrival (DoA) and Departure (DoD) of multipath components (MPCs). Stochastic models describe spatial channel properties by modeling statistics at antenna array elements. A generic MIMO channel model can capture several significant effects: the dependence of receiving array directions of arrival (DoAs) on transmit directions of departure (DoDs), variations in channel spatial properties with different delays in frequency-selective channels, the finite number of scatterers, long-term spatial properties reflecting multipath component characterization, potential rank deficiency in instantaneous MIMO transfer matrices, and the need for adequate channel coverage. These models are broadly classified, as depicted in figure 6, following a similar classification outlined in[37].

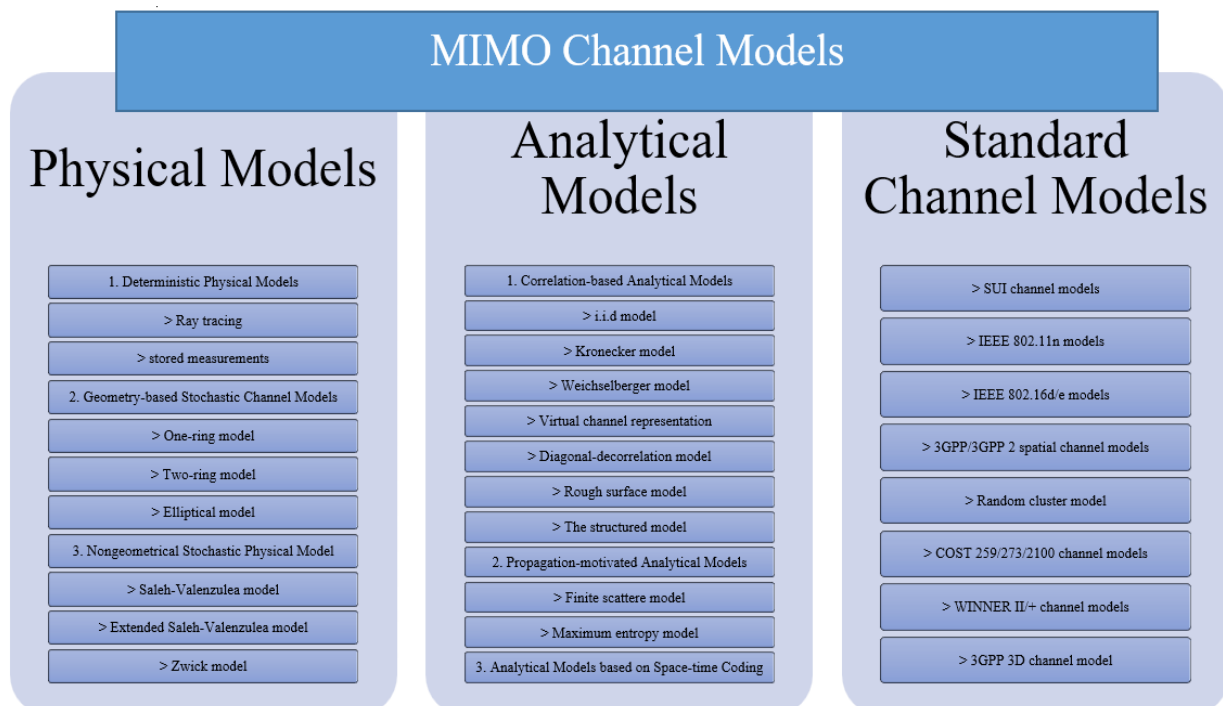


Figure6: Basic Classification of MIMO Channel Models [23]

3.6 Physical Models

Physical channel models delineate the propagation environment through bidirectional electromagnetic wave propagation from transmit to receive arrays. These models facilitate easy modeling of Multipath Component (MPC) parameters' statistics, including Direction of Departures (DoDs), Direction of Arrivals (DoAs), and MPC delays. They represent radio wave propagation parameters as complex amplitude

values. Remarkably, these models remain agnostic to antenna configurations, encompassing factors like antennas, system bandwidth, mutual coupling, antenna pattern, polarization, and array geometry. The mobile spectrum and the joint power spectrum of Base Station (BS) angular spectrum constitute the two spectra products, facilitating the immediate reuse of directional channel models[38]. Geometrical models, assuming single-scattering processes, find

applicability in scenarios where scatterer locations dictate DoA and DoD, particularly in microcellular environments.

3.6.1 Deterministic Physical Models

Deterministic channel models simulate radio propagation characteristics in specific environments to replicate channel transfer and coverage. They find application in deploying or optimizing site-specific radio systems, relying on geometrical environment specifications obtained from digital databases. These models generate detailed outputs of field strength and multidimensional channel transfer functions over network locations, cells, paths, or entire service regions, offering valuable insights into time and space distribution, including propagation delays, departure angles, and multipath arrival[39]. They play a crucial role in planning 4G and 5G networks leveraging MIMO technology. However, limitations such as inaccuracies in database information, challenges in modeling diffuse scattering, and high computational complexity restrict their utility.

(A) Ray-Tracing Algorithm

This algorithm simulates electromagnetic wave propagation in mobile communication channels, employing geometrical optics principles to determine all potential paths between transceivers. It demands significant time, precision, and computational resources due to its exhaustive nature. Typically, a visibility tree is employed to capture individual propagation paths, featuring a structured layout with branches and nodes. Each branch represents a Line of Sight (LoS) link, with the root nodes denoting the transmit antenna. The algorithm operates recursively, tracing paths from transmitter to receiver. Efficient multielement ray tracing has been observed, validated against site-specific measurements for MIMO channel data at 2 GHz in urban settings. However, despite its accuracy, ray tracing is computationally intensive and lacks flexibility, as its outcomes are intrinsically tied to specific site characteristics[40-42].

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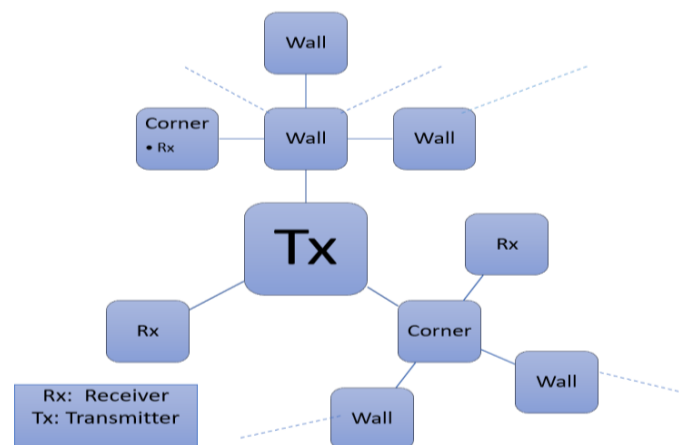


Figure 7: An Illustration of a Ray-Tracing Visibility Tree [61]

(B) Stored Measurements

The stored measurements concept, detailed in [43], involves using a sounder to take measurements and record multiple Single Input Multiple Output (SIMO) snapshots as Fast Doppler Blocks (FDB). Each snapshot includes complex uniform results along with a Uniform Linear Array (ULA). Similar applications of sounders for measurements and storage are discussed in [44]. Channel responses are estimated in real-time and stored as complex frequency responses for later offline

postprocessing on the sounders' hard disk. However, this method is significantly impacted by high memory requirements, and channel responses are inherently site-specific.

3.6.2 Stochastic Models

In this model, statistical methods are used to estimate the spatial characteristics of MIMO-based radio channels, often referred to as channel correlation properties[45]. The steering vector represents a plane wave hitting an antenna array from a specific direction. Stochastic models aim to characterize the MIMO channel

experienced by communication systems using antenna arrays. However, the details of the second-order statistics derived from the full MIMO correlation matrix can be extensive and challenging to interpret directly in terms of physical propagation.

(A) Geometry-Based Stochastic Models (GBSMs)

In this model, scatterers are stochastically distributed across both ends of the link. Utilizing fundamental electromagnetic wave principles of reflection, diffraction, and dispersion, the channel model is derived from scatterer positions, reflecting the shape of the scattering area and providing scenario-specific insights. Careful scatterer distribution around User Equipment

(UE) enables accurate macrocell simulations, while microcells employ ellipses with focal points at the NodeB and UE. Parameters such as scatterer number and clustering are vital for reliable scenario simulation. For instance, evenly distributing scatterers around a circle centered on the UE facilitates uniform Direction of Arrival (DoA) in the azimuth, akin to Clark's Doppler spectrum, enhancing modeling accuracy[46-48].

(B) Geometry-Based Statistical Propagation Models

Geometry-based statistical propagation models, such as the one-ring model, a combined elliptical model, and the one-disk model, are briefly introduced in the discussion.

4443

Table 2: Comparison of Geometry-based Statistical Models

One-Ring Model	Combined Elliptical-Ring Model	One-Disk Model
The predominant geometry-based stochastic channel model adopts an approach that considers local dispersion caused by nearby obstacles in relation to subscriber unit placement within MIMO systems [49].It's worth noting that the one-ring model might not strictly adhere to the widely accepted Kronecker model [74].	The combined elliptical-ring model was developed by integrating isodelay ellipses to define tap delay profiles and angular spreads. It introduces a critical parameter known as the local scattering ratio (LSR), which directly correlates with angular spreading properties [50-51].	This model resembles the geometry-based approach for Line of Sight (LoS) multipath radio channels [52]. It comprises a sizable single disk positioned between a transmitter and a receiver, populated with evenly distributed scatterers. The model's correlation is notably influenced by the path loss exponent.

3.6.3 Nongeometrical Stochastic Physical Models

These models solely establish paths between transmitter and receiver through statistical methods, overlooking the geometric attributes of the physical environment. Examples encompass the Saleh-Valenzuela model, the extended Saleh-Valenzuela model employing Multipath Component (MPC) clusters, and the Thomas Zwick model, which handles individual MPCs.

(A) Saleh-Valenzuela Model

Saleh and Valenzuela [53] introduce a model that provides insights into the arrival times of Multipath Components (MPCs) in the delay domain for wireless time-invariant channels. They segment the channel response into clusters, each containing multiple multipath components. The Saleh-Valenzuela model offers several significant contributions:



1. It is one of the earliest models to incorporate the concept of clustering in relation to multipath phenomena.
2. It models the arrival times of clusters and the multipath components within them as two distinct Poisson processes, each with its own rate.
3. The model demonstrates the decomposition of the received Probability Density Profile (PDP) into various components, including an overall PDP.
4. It shows that both PDPs can be represented as exponentially decaying profiles.

(B) Extended Saleh-Valenzuela Model

During their tenure at Bell Laboratories, Saleh and Valenzuela conducted extensive measurement

campaigns from various fixed indoor locations. They estimated parameters using curve-fitting techniques and discovered that Multipath Component (MPC) clusters could be described in the delay domain by a dual exponential-decay process. The sounder they used employed omnidirectional antennas in the azimuth plane, which did not characterize Angle of Arrival (AoA) and Angle of Departure (AoD). Their work in [54] resulted in a model where multipath components clustered in the delay domain, while in the azimuth domain, they followed a Laplacian distribution. In the extended Saleh-Valenzuela (SV) model, the channel impulse response in the azimuth-elevation space integrates contributions from all multipath components across all clusters [55].

$$h(\tau, \varphi) = \sum_{c=0}^{\infty} \sum_{l=0}^{\infty} a_c \cdot e^{j\varphi_c \cdot l} \delta(\tau - \tau_c - \tau_{c,l}) \delta(\varphi - \varphi_c - \varphi_{c,l}) \dots (4)$$

Here, the variables φ_c and φ represent the azimuth Angle of Arrival (AoA) of the clusters and the Multipath Components (MPCs), respectively. φ_c denotes the average AoA value of all multipath components within the cluster. Both φ_c and φ are considered random variables.

(C) Zwick Model

This model is designed for indoor channel propagation [56] employing a geometry-based method using a birth-death technique to depict multipath component motion over time. It utilizes ray-tracing tools, which can be expensive, for automated parameter extraction in new environments and frequencies, eliminating the need for field measurements. Despite its cost, it supports Monte Carlo simulations for wireless systems, including smart adaptive antennas and modulation. It enables seamless transitions between Line of Sight (LoS) and obstructed LoS (oLoS) configurations by separately modeling the LoS portion from other multipath components. It's also useful for system simulations, evaluating bit error rates (BERs) and configurations involving SDMA, MIMO, and spatial filtering for interference reduction.

3.7 Analytical Models

In this model type, the radio channel's impulse response is depicted individually between transmitters and receivers, lacking comprehensive information on wave propagation. This differs from physical models, which typically illustrate statistics of Multipath Components'

(MPCs) parameters constituting the overall impulse response. Analytical channel models find broad utility in simulation settings due to their ease of generation and effectiveness in representing diverse channel responses. However, these models often do not directly align with the physical environment in which the MIMO system operates and the characteristics of the channel matrix. Generally, these models are categorized into correlation-based and propagation-motivated analytical channel models.

(A) Correlation-Based Analytical Models

(i) The i.i.d Model

The Independent and Identically Distributed (i.i.d) model is often hailed as the simplest MIMO model, also known as the canonical model in certain literature. In this model, $R_h = p^2 I$, where p^2 denotes the channel power and H represents the MIMO channel matrix. This model incorporates the channel power utilized in information theory to analyze MIMO systems. The i.i.d. model involves using multiple elements for a single user across the additive Gaussian channel. Due to its characteristic behavior, this model assumes statistical independence and lacks correlation.

4444



The i.i.d. model, known for its capacity gains, is particularly suitable for theoretical analysis[57].

(ii) Kronecker Model

In this model, the assumption is that scatters at both ends of the link can be treated independently. It approximates the full correlation by using the Kronecker product of one-sided correlation matrices, thereby reducing the required parameters while offering valuable insights into the channel and adding structure to the model. Despite reports suggesting

inaccuracies in practical scenarios, the Kronecker model remains widely used in MIMO channel modeling due to its ease of application and analytical tractability [58]. This model presents the full correlation matrix as the Kronecker product of the two marginal correlation properties at both link ends, resulting in identical Departure and Arrival angles. However, this does not hold true for most practical MIMO channels, leading to inconsistent predictions of channel capacity. The wideband equivalent synthesis equation of the model is provided in [59].

$$H_{Kron} = \frac{1}{\sqrt{\text{tr}\{R_{Rx}\}}} R_{Rx}^{\frac{1}{2}} G (R_{Tx}^{1/2})^T \dots\dots (5)$$

As given in equation, $R_{Tx} = E\{H^T H^T\}$, and $R_{Rx} = E\{H H^H\}$, indicates the correlation matrices for transmission (Tx) and reception (Rx). G is a random fading matrix with independent identically distributed (i.i.d) unity variance, consisting of complex Gaussian variables.

(iii) Weichselberger Model

To enhance the Kronecker model, Weichselberger[60] proposed a more realistic channel model. This model incorporates joint correlation between the transmitter and receiver while preserving dependencies between the Angle of Arrival (DoAs) and Angle of Departure (DoDs). It comprises three components: firstly, the correlation matrix of the spatial eigenbasis of both the transmitter and receiver; secondly, the

eigenmode pair of the receiver and transmitter, spanning the Single Input Single Output (SISO) channel; and finally, the power coupling matrix of each element formed by its average energy. When the coupling matrix aligns with the transmitter's model, it approximates the Kronecker model. The eigenvalue decomposition of the receiver and transmitter correlation matrices are described in below equation.

$$R_{Rx} = U_{Rx} A_{Rx} U_{Rx}^H, R_{Tx} = U_{Tx} A_{Tx} U_{Tx}^H \dots\dots (6)$$

$$H_{Weichsel} = U_{Rx} (\Omega'_{Weichsel} \Theta G) U_{Tx}^T \dots\dots (7)$$

Here, G represents the independent and identically distributed (i.i.d) complex Gaussian random fading matrix, while $\Omega'_{Weichsel}$ denotes the element-wise square root of the power coupling matrix $\Omega_{Weichsel}$.

(iv) Virtual Channel Representation (VCR)

The VCR method aims to characterize the channel within the beam space by employing a predefined steering vector as outlined in Equation 8

$$H_{virtual} = A_{Rx} (\Omega'_{virtual} \Theta G) A_{Tx}^T \dots\dots (8)$$

The variables A_{Rx} and A_{Tx} represent the element-wise square root of the power coupling matrix $\Omega'_{virtual}$ in the virtual domain. The accuracy and angular resolution of the Virtual Channel Representation (VCR) model depend on the number of virtual angles[58]. Notably, these angles cannot be arbitrarily chosen but must be derived from the antenna array configurations. The VCR restricts the eigenbases to predefined Discrete Fourier Transform (DFT) matrices, assuming optimal eigenfunctions for the channel matrix. A key aspect of the VCR is its interpretability, with the antenna configuration dictating its angular resolution accuracy.

(v) Diagonal-Decorrelation Model

The diagonal decorrelation model sets all cross-correlations to zero independently of antenna

correlation values. In this model, the channel matrix $\backslash (R \backslash)$ is assumed to remain semi-positive definite. While detailed explanations are scarce,



this model has been discussed in [61], primarily focusing on its physical rationale.

(vi) Rough Surface Model

Introduced in [62], this model is designed for multiuser MIMO channels, drawing inspiration from Kirchhoff's theory to derive cross-user and intruder correlations for closely situated users. It facilitates the examination of antenna pair correlation among users and within a single user. The model places importance on physical environmental features, such as the roughness and geometry of scattering surfaces. It can be applied to scenarios like users in valleys and scatterers on streets. Valuable for estimating spatial correlation relative to scattering surface profiles and theoretical channel gain limits, this model holds potential for extension to multiuser channel models. Additionally, it offers advantages

in locations where modeling scatterer's random rough surfaces is feasible.

(vii) The Structures Model

This model, an extension of the Weichselberger model, utilizes tensor calculus to describe the coupling of scatterers across the receiver's delay space and the transmitter. It emphasizes three correlation matrices: one each for the receiver, transmitter, and delay space, using tensor calculus. Unlike the Kronecker model, this structured approach does not assume independence between scatterers at the receiver, transmitter, or different delays. This allows for a more accurate approximation of the actual structure of the wideband MIMO channel. Moreover, it requires fewer parameters than the Kronecker model for synthesizing an ensemble of H-tensors [63].

4446

Table 3: A Comparative Description of Some MIMO Channel Models

Models	Suitable environments	Benefits	Limitations
Kronecker	Solely local scatterers	Mathematically simple	A special case of VCR
Virtual channel representation	Scatterers are dispersed based on predetermined angular directions	Considering the influence of scattering parameters on channel diversity and capacity	Necessitating a particular scatter distribution or a sizable array
Weichselberger	Diverse environments	The constraints on VCR are being removed	Clustered antennas are needed at both the transmitter and receiver.
Rough surface model	Extensive planar scatterers	Theoretical calculation of spatial correlation concerning the scattering surface profile and channel gain, extending to multiuser channel modeling.	Limited to particular environments and necessitating certain parameters of the scattering surface.

(B) Propagation-Motivated Analytical Models

Approaches such as the finite scatterer and maximum entropy models are employed to characterize the MIMO channel matrix, incorporating relevant propagation parameters. A concise overview of these models is provided below.

(i) Finite Scatter Model

This prevalent analytical model utilizes a limited number of multipath components to depict the

channel, encompassing both single-bounce and multiple-bounce scattering scenarios. Notably, it accommodates split components, where a single direction of departure divides into multiple paths with different directions of arrival. Fully compatible with the 3GPP spatial channel model, it offers versatile representation capabilities [64].

(ii) Maximum Entropy Model

This model provides the MIMO channel's distribution based on available information,



typically comprising propagation domain features and system parameters like bandwidths and arrival directions. The choice of model impacts its application; channels may vary for capacity estimation versus bit error rate simulation. Overall, the maximum entropy model is straightforward to apply, particularly when it comes to maintaining consistency while translating physical information into the channel's distribution model.

(C) Analytical Models Based on Space-Time Coding

These models are tailored for theoretical analysis of communication systems employing space-time coding, as documented in various literature [65-66]. They detail the communication channel in terms of degrees of freedom, aiding precise capacity analysis. Particularly relevant in the context of emerging 6G networks, they derive limits on spatial degrees of freedom for multi-antenna systems, considering antenna array constraints. They also help determine the optimal number of antennas for specific applications. For instance, [67] illustrates signal clustering in multi-antenna channels, while [68] numerically assesses electromagnetic degrees of freedom in noise-limited systems with multiple random scattering, using the fast multipole method (FMM) and Monte Carlo simulation.

3.8 Standardized Models

In this section, we offer a comprehensive overview of analytical channel models, which serve as a standardized framework for developing new radio systems. These models integrate various techniques, including signal processing and multiple access, to enhance performance and system capacity. For example, the wideband COST 207 power delay profile model is widely used in GSM development, helping to select appropriate modulation and access techniques. Other standardized MIMO models include projects such as COST action projects, 3GPP SCM, WINNER channel, IEEE 802.11n, IEEE 802.16ac, and Stanford University Interim (SUI) models, each briefly outlined below.

(A) COST Action Projects

The European COST action initiative has yielded several models, including those addressing directional features of the wireless channel for MIMO and smart antenna simulations. Beginning with COST 207 and progressing to the emergence of the COST 2100 model, this initiative has significantly contributed to the growth and development of wireless communication systems. Brief descriptions of these models are provided in Table 2.

4447

Table 4: Description of The COST Action Models

Sr.No	COST model	Model description
1	COST 207 channel model	As the first COST action project, this model originated from the Digital Land Mobile Radio Communications project, supporting the CEPT GSM in research coordination for propagation, modulation, and coding. The project involved reviewing existing path loss prediction techniques and meticulously gathering terrain and land cover data to build a comprehensive topographic database.
2	COST 231 Hata model	The COST 231 Hata model extends the widely-used Okumura-Hata model to the 1500-2000 MHz band, addressing scenarios where the Okumura-Hata model underestimates path loss. Detailed specifications of the model are available in previous reports [78-79].



3	COST 231 Walfish-Ikegami model	The COST 231 Walfish-Ikegami model distinguishes between Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) configurations, ideal for microcellular settings. Operating between 800 MHz to 2000 MHz, it covers receiver-transmitter distances from 0.02 km to 5 km. Additional parameters and scenarios are detailed in various reports.
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(B) 3GPP Spatial Channel Models

The 3GPP Spatial Channel (SCM) model aids simulations for macrocell and microcell deployment in 3G networks with a 5MHz bandwidth [69]. It assigns constant values to azimuth spread, Directions of Arrival (DoAs), and Directions of Departure (DoDs), considering user device movement within coverage areas. Interference is categorized as strong or weak, with strong interferers modeled as spatially correlated. An extended version, compatible with emerging technologies beyond 3G, is discussed in [70]. It classifies urban micro, urban macro, and suburban macro environments, each with specific propagation characteristics. Urban micro environments account for both Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) scenarios, with six fixed paths and twenty subpaths spatially separated. This model is derived from the sum-of-sinusoids method.

(C) The COST 259/273/2100Channel Models

The COST action projects have produced several influential channel models, including COST 259, which emphasizes the intricate interplay between propagation distance, angular spread, delay dispersion, and various channel parameters[71]. This model aims to accurately depict the characteristics observed in measured data while maintaining compatibility with earlier iterations and ensuring computational efficiency. Similarly, the COST 273 model, an extension of COST 259, introduces a statistical framework for multipath components' amplitude, phase, Angle of Arrival (AoA), Angle of Departure (AoD), and delay, with specific emphasis on clustered multipath scenarios. Unlike its predecessor, the COST 273

model offers physical interpretations for its parameters, derived from measured data, facilitating a deeper understanding of the environment[72]. Additionally, the COST 2100 model builds upon the foundations laid by COST 259 and COST 273, extending its capabilities to simulate multilink MIMO channels across time, frequency, and space. Notably versatile, this model accommodates multicell MIMO scenarios and includes features like multipath component polarization modeling and dense multipath contributions[74-75]. It focuses on detailed descriptions of clusters, scattering characteristics, and large-scale parameter statistics, ensuring robustness and accuracy in replicating channel propagation scenarios.

(D) The Random Cluster Model

To address limitations of the COST 273 model, researchers proposed the random cluster model (RCM) in [73]. Unlike its predecessor, RCM offers automatic cluster parameter identification from measured data and characterizes clusters using a multivariate Probability Density Function (PDF) termed the environment PDF. Unlike the COST 273 model, which varies across environments, RCM ensures uniform characterization using the environment PDF, reducing implementation complexity. RCM automatically computes the environment PDF from measured data, aligning closely with the specific environment and measurement routes. Its benefits include accurate channel time variation simulation, tracking clusters over time, and system independence. However, computing the environment PDF poses a challenge.

4448

(E) WINNER Channel Models

Table 5: Comparison of WINNER Channel Models

Interim WINNER Channel Model	WINNER II Multilink MIMO Channel Model
The interim WINNER model extended the SCM to encompass intra-cluster delay spreads, Line-	The WINNER II model evolved from its predecessor, the initial WINNER model. Unlike the SCM model,



of-Sight (LoS), and K-factor models across all scenarios. This was achieved by initially defining various large-scale parameters including Ricean K-factor, spreading delay, shadowing standard deviation, and spreading directions at both departure and arrival [76]. The WINNER channel model implies that successive channel matrices can be generated in brief segments, with each segment corresponding to a sample of large-scale parameters.	which conducts separate simulations for each connection, WINNER II allows for the simultaneous stimulation of multiple links between Base Stations (BSs) and Mobile Terminals (MTs) [77]. This capability arises due to correlation being treated as a distance feature in multi-segment scenarios. Notably, the modified WINNER model facilitates the derivation of large-scale statistics for various realization scenarios.
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(F) SUI and IEEE 802.xx Channel Models

able 4 showcases the SUI and IEEE 802.xx channel models, which encompass the IEEE 802.11n, IEEE 802.16a, and IEEE 802.16d/e channel models.

Table 6: A Brief Description of The SUI And IEEE 802.xx Channel Models

Sr.No	Channel Models	Brief description
1	Stanford University Interim channel model	The SUI model, developed at Stanford University, aligns with IEEE 802.16 standards for fixed wireless access (FWA) systems. It classifies terrain into types A, B, and C, each addressing specific path loss characteristics. Type A suits hilly regions with significant path loss, while type C is for minimal loss in flat areas. Type B is suitable for hilly terrain. Details, including path loss equations and correction factors, are provided in [80]. Additionally, the SUI models apply a rounded shape centered around zero to each tap's Doppler spectrum, providing limited information compared to the Jakes spectrum.
2	IEEE 802.11n channel models	IEEE 802.11n, derived from the extended SV model, offers simplified versions suitable for bandwidths up to 100 MHz. It's particularly applicable in indoor MIMO LAN networks operating at 2 GHz and 5 GHz. This model systematically covers six canonical channels, addressing various scenarios including flat fading, residential, traditional workplace, large office, small office, and large open spaces.
3	IEEE 802.16a channel models	After adapting the popular SUI channel models, the IEEE 802.16 models were developed for directional and omnidirectional antennas. These models enhance Ricean tap K-factors and reduce global delay spread. Notably, the IEEE 802.16a model preserves user terminal correlations while narrowing antenna beamwidth. It categorizes path loss into three terrain types: hilly with moderate-to-heavy tree densities (A), intermediate path loss (B), and mostly flat with light tree densities (C). These correspond to SUI models 5 and 6 (A), 3 and 4 (B), and 1 and 2 (C) respectively [1]. Spatial channel models based on this standard have been established [81].
4	IEEE 802.16d/e channel models	The IEEE 802.16d/e models, an evolution of the interim SUI channel model, cater to fixed macrocellular connectivity.

4449



		Accommodating both directional and omnidirectional antennas, they enhance the global K-factor while reducing delay distribution. Classified into three categories (Type A, B, and C), they consider obstacle density, like tree coverage, in micro-suburban settings. MIMO channel models in the IEEE 802.16e standard are standardized by the WiMAX Forum, detailed in numerous reports [82-83] .
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5.LITERATURE SURVEY

The table below provides an overview of the literature survey pertaining to channel modeling and estimation techniques.

Table 7: Literature Review

Authors	Paper title	Major findings	Research methodology used	Research prospects
Amir Hossein et al	UAV Channel Estimation with STBC in MIMO systems	The utilization of STBC coding schemes in MIMO systems demonstrates improved performance in comparison to MISO systems within the Rayleigh fading channel.	Utilizing Kalman Filtering with STBC Codes for Encoding and Decoding, Alongside Channel Estimation Technique Based on Pilot Subcarriers.	Complexity of STBC decoding and coding rises linearly with the number of transmitter and receiver antennas.
Akansha Gautam et al	Efficient Wireless Channel Estimation using Alamouti STBC with MIMO and 16 PSK modulation.	Outperforming MISO with 16-PSK Modulation in Employed MIMO System	Plotting BER Curves for Increased Signal Power with Multiple Receivers (M) Equal to or Less Than Transmitters for 2xM and 4xM Systems.	Employing More Efficient Modulation Technique for Better Outcomes.
G. Rajender	Empirical analysis of channel estimation procedures with enhanced Kalman filter algorithm over MIMO-OFDM environment	Suggesting Enhanced Kalman Filter Algorithm for MIMO-OFDM Channel Estimation.	Utilizing Probability and Computer Simulation Techniques	Enhanced Kalman Filter: Supporting Large-Range Wireless Communication with QoS-Level Accuracy.
Mahdi Abdul Hadi et al	MIMO-OFDM with Enhanced Channel Estimation based on DFT Interpolation	MMSE Estimator Outperforms LS Estimator in MIMO-OFDM Systems, Enhanced LS and MMSE Estimators	Proposing DFT Interpolation-Based Channel Estimation with LS and MMSE Estimation Techniques.	Improving Estimation Performance by Increasing Pilot Count.

4450



		Using DFT-Based Technique.		
Parismita Gogoi et al	Channel Estimation Technique for STBC Coded MIMO System with Multiple ANN Blocks	RNN Networks Outperform MLP Networks Due to Loop Presence	Training Two Different ANN Structures: Multilayer Perceptron (MLP) and Recurrent Neural Network (RNN) with LM and Quasi-Newton Algorithms.	Extending the Work: Designing an Optimized Channel Estimator through a Hybrid Approach with ANN and Neural Fuzzy System.
A. L. Sulyman et al	Performance of MIMO Systems with Antenna Selection Over Nonlinear Fading Channels	Antenna Selection: Optimizing Performance Trade-Offs in MIMO Systems	Proposing Reduced Complexity Space-Time Coding System for Pairwise Error Probability (PWE) Performance.	Analyzing Antenna Selection on the Transmitter Side.
S. G. Kim et al	Performance analysis of the MIMO zero-forcing receiver over continuous flat fading channels	BER Performance Depending on Doppler Spread and Channel Estimation Error, Enhanced with Larger Antenna Discrepancy.	Designing Zero-Forcing Receiver and Transmitter	Designing ZF Receivers for Nonlinear Fading Channels
C. Wang et al	On the Performance of the MIMO Zero-Forcing Receiver in the Presence of Channel Estimation Error	High SNR Leads to Imperfect Channel Estimation, Preventing BER from Approaching Zero.	Analyzing BER Performance Using SNR Distribution	Minimizing Channel Estimation Errors
X. Zhang et al	Performance Analysis of Multiuser Diversity in MIMO Systems with Antenna Selection	Designing Efficient Scheduling Methods for Multiuser TAS/MRC Systems.	Utilizing Various Computer Simulation Techniques.	Providing Verifiable Theoretical Explanations.
Hemlata Sinha	BER performance analysis of MIMO-OFDM over wireless channel	Designing a Method for MIMO Orthogonal Space-Time Block-Coded OFDM Systems.	Utilizing Computer Simulation Techniques.	Achieving High Data Rates Without Increasing Channel Bandwidth.
Imran Khan et al	A robust channel estimation	Efficient CSI Acquisition	Utilizing the Channel Matrix Separation	Channel Estimation with Reduced Pilot



	scheme for 5G massive MIMO systems	Technique with Reduced Pilot Overhead.	Mechanism.	Overhead and Enhanced Performance Compared to State-of-the-Art Schemes.
A. N. Uwaechia	Spectrum-efficient distributed compressed sensing-based channel estimation for OFDM systems over doubly selective channels	Introducing a Tensor-Based MMSE Channel Estimator and Tensor-CS Model	Formulating a Tensor-Orthogonal Matching-Pursuit (T-OMP) Estimator Approach.	Exploring the Multidimensional Frequency-Selective Massive MIMO Channel Through 3D Sparse Representation in the Frequency Domain.
A. L. Ha	Deep learning – aided 5G channel estimation	Proposing a Novel Channel Estimation Method with Deep Learning Support for LS Estimation.	Utilizing a Multi-Path Channel Profile in Simulated MIMO Systems	Low-Cost Method Yields Relatively High Channel Estimation Error.
I. Khan	Computationally efficient channel estimation for 5G massive MIMO systems	Proposing a Computationally Efficient Hybrid SDGS Joint Detection Method	Log-likelihood ratio and various computer simulations are used.	The user's transmitted symbol vector, signal detection performance is improved.
H. Sinha	BER performance analysis of MIMO-OFDM over a wireless channel	A Method for MIMO OSTBC-OFDM System	Computer simulation techniques are used.	Preserving Channel Orthogonality in MIMO-OFDM Enhances System Performance.

4452

6. CHANNEL ESTIMATION TECHNIQUES

In wireless communication, channels are pivotal, facilitating data transfer between mobile or fixed transmit and receive devices. Channel estimation becomes crucial to recover signal properties at the receiver amidst multipath propagation and time-varying channels. Perfect and timely channel estimation is vital for accurate signal reconstruction, equalization, decoding, and demodulation. Prior research has focused on

developing efficient channel estimation techniques for various wireless and mobile communication scenarios, employing diverse transmission and modulation schemes. These techniques broadly fall into three categories: pilot-assisted (training-based) channel estimation, blind and semi-blind channel estimation schemes, and decision-directed channel estimation (DDCE).



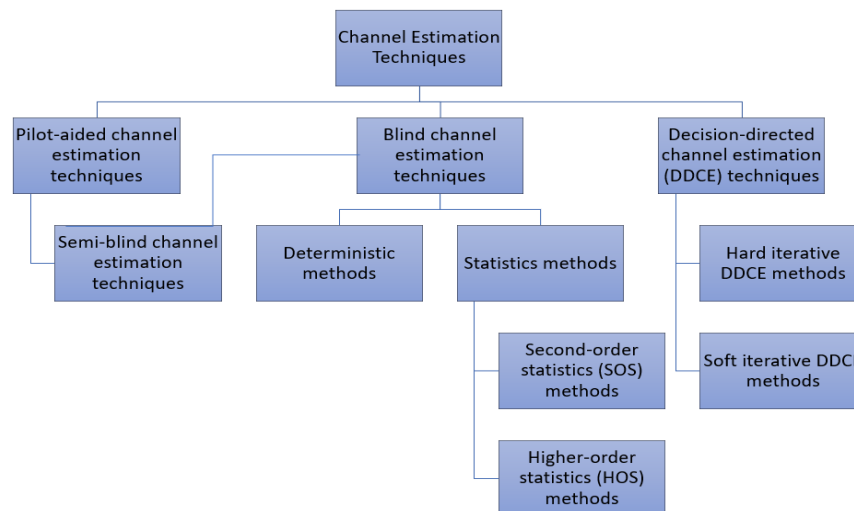


Figure 8: Channel Estimation Techniques Classification [84]

4453

6.1 Pilot Arrangement/ Structure

MIMO-OFDM systems commonly utilize pilot arrangements, with 'Block type' and 'Comb type' being the most prevalent. The following section provides a brief overview of these two pilot arrangement types[85-86].

(A) BLOCK TYPE -This pilot arrangement entails fixed pilots designed for each subcarrier, placed orthogonally and transmitted periodically. These pilot symbols aid in channel estimation and original signal detection at the receiver. Such an arrangement is typically employed in scenarios where the channel varies slowly over OFDM symbols, such as in slow-fading channels.

(B) COMB TYPE –This pilot arrangement involves re-inserting pilot symbols into a set of OFDM symbols at fixed positions. Channel estimation is performed using these pilot symbols, and interpolation techniques are applied to estimate other symbols known as data symbols. This arrangement is suitable for fast-fading channels.

(C) LATTICE TYPE – In the lattice-type pilot arrangement, illustrated in Figure 9, pilot tones are inserted along both time and frequency axes at specified intervals. These pilot tones, spread across both time and frequency axes, enable time/frequency-domain interpolations for channel estimation. This arrangement is also referred to as the scattered-type pilot arrangement.

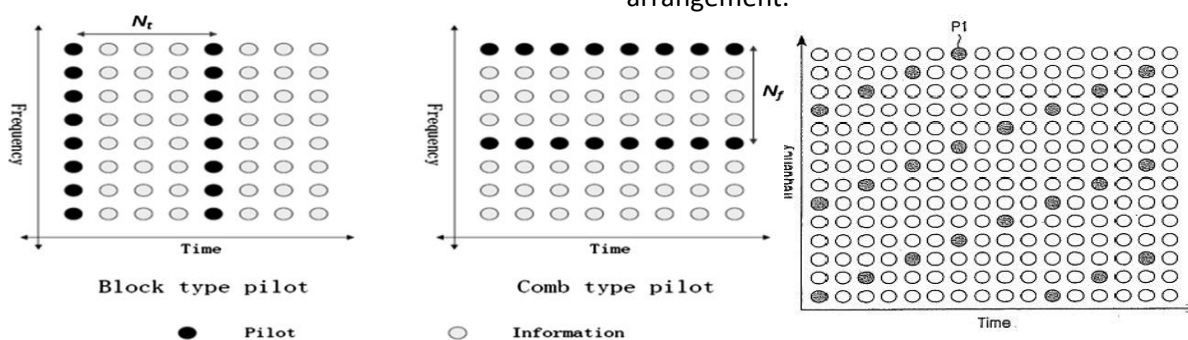


Figure 9: Pilot Arrangement i) Block Type, ii) Comb Type, (iii) Lattice type [87]

6.2 Pilot-Assisted Channel Estimation Technique

This approach, known as training-based channel estimation, is a conventional method for acquiring channel estimates in communication systems. Training sequences of known data are combined with transmitted information symbols

at predetermined positions before transmission. The receiver uses this training data to estimate the Channel State Information (CSI) for its position. CSI for the information data positions is then derived by interpolating between the different channel estimates obtained from the

training data sequence. However, this method incurs higher overhead due to the use of pilot symbols. To address this issue, techniques like the

Least Squares (LS) estimate and Minimum Mean Square Error (MMSE) algorithms are employed.

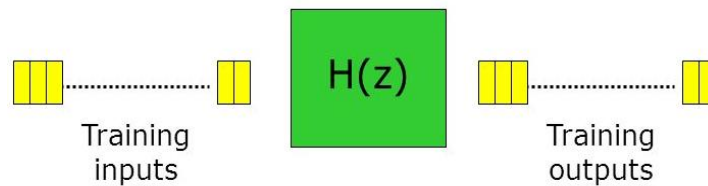


Figure 10: Model for Training Symbol-Based Channel Estimation [88]

Pilot symbol-based channel estimation operates by strategically inserting known pilot symbols into the transmitted data stream at regular intervals. These pilot symbols serve as reference points for estimating the characteristics of the communication channel at the receiver. Upon reception, the received pilot symbols are compared with their transmitted counterparts, allowing the receiver to infer channel response characteristics such as multipath fading, phase shifts, and amplitude variations. Interpolation techniques are then employed to estimate the channel response for non-pilot symbols based on neighbouring pilot symbols. This process enables the receiver to accurately reconstruct the transmitted signal, compensating for distortions introduced by the channel.

Pilot symbol-based channel estimation offers several advantages in wireless communication systems. By strategically inserting known pilot symbols into the transmitted data stream, this technique provides a robust reference for estimating channel characteristics such as multipath fading, phase shifts, and amplitude variations at the receiver. Moreover, pilot symbol insertion typically incurs minimal overhead compared to other channel estimation methods, making it suitable for real-time applications.

(i) Least Square (LS) Estimator

In an OFDM system, the signal received at the receiver can be characterized as:

$$Y = HX + W \quad \text{..... (9)}$$

Where $H = [H[0], H[1], \dots, H[N-1]]^T$ is the vector form of channel,

$W = [W[0], W[1], \dots, W[N-1]]^T$ is the vector form of noise with 0 mean and σ^2 variance and

$$X = \begin{bmatrix} X(0) & 0 & \dots & 0 \\ 0 & X(1) & \dots & \dots \\ \dots & \dots & \dots & 0 \\ 0 & \dots & 0 & X(N-1) \end{bmatrix} \quad \text{..... (10)}$$

The least square estimation for 5G multicarrier wireless communication in Rayleigh and Rician fading channels is given by

Additionally, pilot symbol-based techniques exhibit adaptability to dynamic channel conditions, allowing for adjustments in the insertion rate and placement of pilot symbols as needed. However, pilot symbol-based channel estimation also has its limitations. One major disadvantage is its susceptibility to interference from neighboring symbols or adjacent channels, which can adversely affect the accuracy of channel estimation. Furthermore, while pilot symbols minimize overhead compared to other techniques, they still consume bandwidth and reduce data throughput, particularly in bandwidth-constrained scenarios. Additionally, the interpolation techniques used for channel estimation may introduce computational complexity, especially in systems with high mobility or rapidly changing channel conditions, thereby impacting overall system performance.

(A) Channel Estimation Based on Block Type Pilot Arrangement

The OFDM channel estimation symbols are transmitted at regular intervals, employing a block-type pilot-based approach where all subcarriers serve as pilots. Channel estimation can be executed using either the Least Squares (LS) or Minimum Mean Square Error (MMSE) techniques [1-2].

4454

$$\hat{H}_{LS} = (X^H X)^{-1} X^H Y = X^{-1} Y \dots (11)$$

Where estimate of H is $\hat{H}$ and X^H is the Hermitian matrix of X.

(ii) Minimum Mean Square Error (MMSE) Estimator

For an OFDM system the received signal (at the receiver) may be described as

$$Y = HX + W$$

Where $H = [H[0], H[1], \dots, H[N-1]]^T$ is the vector form of channel,

$W = [W[0], W[1], \dots, W[N-1]]^T$ is the vector form of noise with 0 mean and v^2 variance and

$$X = \begin{bmatrix} X(0) & 0 & \dots & 0 \\ 0 & X(1) & \dots & \dots \\ \dots & \dots & \dots & 0 \\ 0 & \dots & 0 & X(N-1) \end{bmatrix}$$

MMSE channel estimation for 5G multicarrier wireless communication in Rayleigh and Rician fading channel is given by

$$\hat{H}_{MMSE} = R_{HH} [R_{HH} + (XX^H)^{-1} Wv^2]^{-1} \hat{H}_{LS} \dots (11)$$

Where R_{HH} is the matrix form of auto-covariance of X

(iii) M-Estimator

An M-estimator is employed to enhance the robustness of the channel estimation approach for 5G wireless communication systems. The penalty, influence, and weight functions of the M-estimator [1-2] for channel estimation in 5G multicarrier wireless communication, considering both Rayleigh and Rician fading channels, are provided by

$$\rho_{PROPOSED}(x) = \begin{cases} \frac{x^2}{2} & \text{for } |x| \leq a \\ a^2 - a|x| & \text{for } a < |x| \leq b \\ -\frac{ab}{2} \exp\left(1 - \frac{x^2}{b^2}\right) + d & \text{for } |x| > b \end{cases} \dots (12)$$

$$\varphi_{PROPOSED}(x) = \begin{cases} x & \text{for } |x| \leq a \\ \text{assign}(x) & \text{for } a < |x| \leq b \\ \frac{a}{b} x \exp\left(1 - \frac{x^2}{b^2}\right) & \text{for } |x| > b \end{cases} \dots (13)$$

$$w_{PROPOSED}(x) = \begin{cases} 1 & \text{for } |x| \leq a \\ \frac{\text{assign}(x)}{x} & \text{for } a < |x| \leq b \\ \frac{a}{b} \exp\left(1 - \frac{x^2}{b^2}\right) & \text{for } |x| > b \end{cases} \dots (14)$$

Where a and b are any constants and x are any data. From an influence function, robustness measures are derived and a ($=kv^2$) and b ($=2kv^2$) are selected (where k is any constant). M-estimator reduce the outcome of outliers with $\min \sum_i \rho(x_i)$, where $\rho(\cdot)$ is penalty function, $\varphi(x) = \frac{d\rho(x)}{dx}$ is the influence function and $w(x) = \frac{\varphi(x)}{x}$ is the weight function.

This technique estimates channel parameters for 5G multicarrier wireless communication in Rayleigh and Rician fading channels using

$$\hat{H}_{PROPOSED} = (X^H \varphi(x) X)^{-1} X^H Y \dots (15)$$

Where $\varphi(x)$ is influence function of the estimator described in above section.

(B) Channel Estimation Based on Comb-Type Pilot Arrangement

For comb-type pilot-based channel estimation, the N_p pilot signals are uniformly inserted into A(k) according to the equation

$$A(k) = A(lM + m) \quad m = 0, 1, \dots, M-1 \\ = \begin{cases} A_p(k) & m = 0 \\ \text{inf. Data} & m = 1, 2, \dots, M-1 \end{cases} \dots (16)$$

Where M = Number of subcarriers (N)/No. of pilot (N_p) and l = pilot carrier index

(i) Piecewise Constant Interpolation



The channel is estimated using the preceding pilot in the piecewise constant interpolation method. Subsequently, the channel estimation is articulated as:

$$\hat{H}(k) = \hat{H}(lM + m) = \hat{H}_p(l), \dots (17) \quad 0 \leq m \leq M, \quad l = 0, 1, \dots, N_p - 1$$

Where M = Number of subcarriers (N)/No. of pilot (N_p) and l = pilot carrier index

(ii) Linear Interpolation

Linear interpolation outperforms piecewise constant interpolation. The channel estimation at the data carrier

k is then expressed as:

$lM < k < (l+1)M$, using linear interpolation is given by:

$$H(k) = H(lM + m) \dots (18) \quad 0 \leq m \leq M, \quad l = 0, 1, \dots, N_p - 1$$

$$= (H_p(l+1) - H_p(l)) \frac{m}{M} + H_p(l)$$

(iii) Second Order Interpolation

The channel estimation at the data subcarrier involves a linear combination of three adjacent pilots in the second-order interpolation technique, which exhibits superior performance compared to linear interpolation. The resulting channel estimation using second-order interpolation is as follows:

$$\hat{H}(k) = \hat{H}(lM + m) = d_1 \hat{H}_p(l-1) + d_0 \hat{H}_p(l) + d_{-1} \hat{H}_p(l+1), \dots (19) \quad l = 0, 1, \dots, N-1, \quad 0 \leq m \leq M,$$

Where M = Number of subcarriers (N)/No. of pilot (N_p) and l = pilot carrier index

(iv) Cubic Spline Interpolation

The cubic spline interpolation is given by [125]

$$\hat{H}(k) = \hat{H}(lM + m)$$

$$= c_1 \hat{H}_p(l+1) + c_0 \hat{H}_p(l) + M c_1 \hat{H}'_p(l+1) - M c_0 \hat{H}'_p(l), \dots (20) \quad 0 \leq m \leq M, \quad l = 0, 1, \dots, N_p - 1$$

Where M = Number of subcarriers (N)/No. of pilot (N_p) and l = pilot carrier index

4456

(v) Time Domain Interpolation

The time-domain interpolation employs zero padding (ZP) and Discrete Fourier Transform (DFT)/Inverse Fourier Transform (IDFT). Once the estimated channel $\{H_p(k), k=0, 1, \dots, N_p-1\}$ is obtained, it is converted to the time domain using IDFT. Subsequently, utilizing basic multi-rate signal processing properties, the signal is interpolated, transforming the N_p points into N points. The estimation of the channel at all frequencies is then achieved by:

$$H(k) = \sum_{n=0}^{N-1} J_N(n) e^{-j(2\pi/N)nk}, \quad 0 \leq k \leq N-1 \quad \dots (21)$$

6.3 Blind and Semi-Blind Channel Estimation Techniques

Due to the inefficiency of bandwidth caused by irregular pilot-assisted channel estimation techniques outlined earlier, alternative methods such as blind channel estimation have been explored. These techniques estimate the channel by leveraging inherent information from both received and transmitted signals. In semi-blind channel estimation, information from known training symbols and inherent data in unknown received signals is utilized. Blind channel estimation methods are typically categorized as statistical or deterministic. Statistical approaches rely on cyclic statistical properties of received signals for channel estimation, while deterministic methods do not utilize statistical properties and

instead treat received signals and channel coefficients as deterministic quantities[92].

Proposed for MIMO-OFDM systems, the blind subspace channel estimation employs a block matrix scheme [93]. This scheme aggregates received OFDM symbols into vectors, facilitating convergence within a limited number of symbols. Semi-blind channel estimation combines pilot sequences with the subspace method to reduce overhead and enhance transmission efficiency for Poisson channels [94]. Initially, fractionally spaced equalizers based on the modified Constant Modulus Algorithm (CMA) and subspace (SS) techniques are proposed. A Data-Aided Iterative Channel Estimation (ICE) method is developed for asymptotic unbiasedness and convergence analysis.



Alternate EM algorithms with suitable priors on channel coefficients outperform those with no priors in low SNR scenarios. Cramer-Rao bounds (CRBs) provide insights into the performance of semi-blind channel estimation for deterministic and stochastic data symbol models. Analyzing CRB behavior with increasing antennas at the base station informs massive MIMO systems. Additionally, a semi-blind iterative space-alternating generalized expectation maximization (SAGE)-based channel estimator is proposed, using data symbols for accuracy enhancement[94-95].

Alternatives to pilot-based channel estimation, like semi-blind and blind methods, offer solutions for mitigating pilot contamination in massive MIMO. MATLAB simulations with a COST 2100 model compare their performance, highlighting their efficacy in addressing pilot contamination challenges [96]. A semi-blind approach combines transmitted pilots and received data samples, enhancing estimation via Gaussian maximum likelihood (GML) criterion and iterative methods [97-98]. Novel semi-blind estimators, leveraging expectation maximization (EM) and decision-directed (DD) strategies, tackle memory effects and channel noise [99-100]. However, traditional semi-blind schemes based on eigenvalue or singular value decomposition face complexity issues. To address this, an adaptive semi-blind estimator employing fast subspace tracking is introduced [101]. Space-time-frequency coded MIMO-OFDM systems achieve spectral efficiency and lower error rates, with semi-blind receivers exploiting multilinear structures for joint channel

and symbol estimation. These techniques, like LS-KRF and S-CFP, reduce system complexity by eliminating the need for a pilot frame. Moreover, semi-blind MIMO-FBMC estimators significantly decrease mean squared error (MSE) by leveraging second-order statistical properties, enhancing spectral efficiency with fewer training symbols[102-103].

Statistical blind channel estimation methods for single-antenna OFDM systems, such as correlation techniques and cumulant fitting, have been extensively researched [104-105]. Utilizing the redundancy of OFDM cyclic prefixes, various blind channel estimation approaches have been devised, alongside different subspace methods [106]. Employing a finite alphabet approach, blind channel estimation is implemented for OFDM systems, with further investigation into blind channel estimation for IEEE 802.11a, exploring clustering techniques. For coded OFDM systems, an Iterative Bayesian method alternating between channel estimation and symbol detection is proposed, while deterministic blind channel estimation approaches based on maximum likelihood principles are developed[107-111]. Deterministic methods offer faster processing compared to statistical counterparts, which may suffer from data effects in short sample sequences, and generally require longer data records, leading to slower convergence rates. While most existing blind and semi-blind methods for MIMO-OFDM channel estimation rely on second-order statistics, advancements such as subspace-based estimators are proposed to address mobility challenges [6].

4457

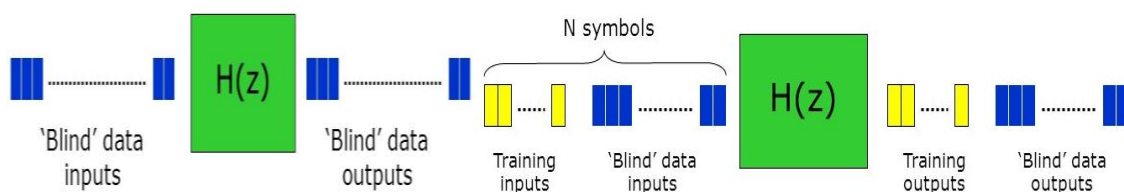


Figure 11: Model for Blind Channel Estimation and Semi-Blind Channel Estimation [88]

6.4 Decision-directed Channel Estimation Techniques

In decision-directed channel estimation techniques (DDCE), both pilot symbols and re-modulated detected message symbols are utilized for channel estimation [114]. When transmission errors are absent, DDCE can function similarly to pilot-assisted channel estimation schemes,

effectively utilizing almost all pilot information symbols compared to schemes employing sparse pilot symbols for the same channel. DDCE reduces the number of pilot symbols required for channel estimation, initializing the process with just a few pilot symbols. The operation of DDCE involves estimating an initial a posteriori channel transfer function (CTF) based on the current detected



symbol, using both pilot symbols and re-modulated message symbols. This a posteriori CTF then serves as an a priori channel estimate during the demodulation of subsequent symbols received in the next time slot.

For coherent optical orthogonal frequency division multiplexing (OFDM) systems, two-phase estimation methods have been proposed: the decision-aided (DA) plus pilot-aided (PA) scheme and the DA plus decision feedback (DF) scheme [115]. In systems with multiple transmit antennas, matrix inversion complexity is addressed with an iterative method [116]. Utilizing the 3GPP Long-Term Evolution (LTE) pilot structure, LS channel estimator performance is enhanced by employing the decision-directed (DD) space-alternating generalized expectation-maximization (SAGE) algorithm and MMSE filtering, reducing pilot overhead while improving data throughput [117-118]. This method involves data detection and successive refinement in channel estimation based on subcarriers with the highest expected signal-to-noise ratio (SNR). Extensions to multiple receive antennas are explored. The MU-MIMO transmission technique promises higher spectral efficiency but struggles with limited CSI knowledge, leading to residual multiuser interference. Employing virtual pilot symbols for channel estimation and leveraging iterative detection and decoding (IDD) schemes can enhance accuracy in such scenarios [119]. For DDCE in OFDM systems, novel techniques like FDPD-based CIR estimation and VSSNLMS-based prediction improve performance under realistic channel conditions. Hybrid approaches, combining PSACE, ICSA, and DDCE, address error propagation in fast-fading environments [120-122]. MIMO-CEM poses challenges due to channel variations. An adaptive CDM-based channel estimator offers iterative estimation in static and quasi-static conditions, while extending to DDCE for dynamic scenarios, showcasing the effectiveness of MIMO-CEM in diverse channel conditions [123-124].

In OFDM systems with transmit diversity, DDCE faces challenges due to the high computational complexity of simultaneously estimating channel responses between the receiver and all

transmitters. To address this, exploiting the correlation of the channel frequency response at adjacent subcarriers can help decouple inter-antenna interference (IAI). By applying unbiased linear estimation methods independently to decoupled IAI data, DDCE performance improves, especially considering unequal noise variances. In iterative DDCE schemes, the channel estimator refines estimates using increasingly accurate symbol information from the detector/equalizer or decoder, enhancing estimates with each iteration. This iterative process enhances both the channel estimator and the detector/equalizer or decoder, operating in tandem for improved performance. Depending on whether hard or soft symbol information is used, these schemes are termed hard or soft iterative channel estimation, respectively [125-128].

In [129], a turbo MIMO OFDM receiver is proposed, which incorporates a soft-feedback decision-directed MIMO channel estimator, a soft-input-soft-output space-time detector, and a soft-input-soft-output parallel-concatenated turbo decoder. These components exchange soft bit-related information iteratively. The soft-feedback decision-directed MIMO channel estimator utilizes the Recursive Least Squares (RLS) algorithm for the Channel Transfer Function (CTF) estimator, distinguishing it from [112-113]. It includes RLS-based CTF estimator, PASTd-based Channel Impulse Response (CIR) estimator, and RLS-based CIR predictor. Comparative results in [130] demonstrate soft feedback iterative DDCE schemes with Turbo codes and Low Density Parity Check (LDPC) codes for channel error correction. However, the complexities associated with RLS and PASTd algorithms may make the proposed estimator impractical.

For less complex alternatives, [133-135] present DDCE and iterative DDCE techniques suitable for both SISO-OFDM and MIMO-OFDM systems. [129] also introduces a Genetic Algorithm (GA)-assisted iterative approach for joint channel estimation and multi-user detection [131] in multi-user MIMO Space Division Multiple Access (SDMA) OFDM systems, addressing scenarios with rank deficiency. Additionally, [132-133] proposes an iterative receiver for MIMO OFDM systems, focusing on joint Inter-Carrier Interference (ICI)



cancellation and channel estimation to effectively compensate for interference in mobile transmission scenarios.

In conclusion, while semi-blind channel estimation techniques, leveraging both unknown data statistics and known pilot signals, offer improved performance compared to standalone pilot-based and blind channel estimation methods [74], they are surpassed by DDCE techniques and their iterative counterparts discussed in this section. When the same number of pilot symbols are allocated to both semi-blind and iterative (decision-directed) channel estimation techniques, the latter demonstrate superior performance, outstripping semi-blind methods and significantly surpassing blind and pilot-assisted channel estimation techniques.

7. CONCLUSION

This paper provides an overview of channel models and estimation techniques tailored for the MIMO-OFDM 5G wireless communication system. Effective communication hinges on accurate reconstruction of received signals, underscoring the critical importance of channel estimation. Firstly, the paper delves into the features of channel estimation. Secondly, it offers a concise overview of OFDM and MIMO-OFDM, alongside massive MIMO systems, as contemporary technologies pivotal for high data transfer rates and improved communication quality, widely employed in modern wireless communication. Understanding channel models is imperative for accurate estimation, thus the paper extensively discusses MIMO channel models. Starting with the fundamental MIMO channel model, it outlines key requirements for MIMO channel modeling, channel sounding and classifications of MIMO technology. Additionally, the paper provides a comprehensive overview of prominent channel models crucial for wireless communication systems, broadly categorized as physical, analytical, and standardized channel models. Furthermore, it explores various channel estimation techniques, including pilot-aided, blind and decision-directed methods, along with discussions on pilot arrangement and types. Lastly, it elucidates numerous channel estimation algorithms based on pilot-assisted techniques, offering detailed insights into their workings.

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