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Original Article

Adaptive Scaling and Spectrum-Aware Enhancement of O-LSDC for Robust MIMO Detection under Realistic Channel Conditions

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Abstract *- Multiple-Input Multiple-Output (MIMO) systems have significant difficulties observing in strong signals because of inter-antenna interference, channel estimation errors, and signal-propagation errors due to the use of iterative cancellation-based detectors. These problems decrease the accuracy of detection and performance in different SNR and CSI. The paper proposes an ingenious detection system that involves adaptive scaling with spectral-domain analysis, which is known as Enhanced O-LSDC, as a way of eliminating these limitations. The method combines mutually adaptive scaling in which the cancellation mechanism is dynamically changed as a function of real-time SNR, CSI, and network behavior. It is also extended to deal with realistic impairments like imperfect CSI, multi-user interference, and error-propagation estimation, and also performs an analysis in the spectral domain to investigate signal distribution, coding energy, and spectral efficiency. The results of the simulation indicate that the proposed Enhanced O-LSDC outperforms the conventional fixed-scaling techniques in terms of bit-error rates and spectral efficiency, as well as offers more CSI uncertainty tolerance and performance variation with a wide range of SNR and channel conditions. These results suggest that the adaptive-scaling-based O-LSDC is a high-quality and computationally small detection strategy that can be used in next-generation wireless systems to support the demands of emerging 5G/6G MIMO structures.*

Keywords *- MIMO, O-LSDC, Adaptive scaling, SNR, CSI, Spectrum analysis, 5G/6G.*

1. Introduction

Over recent years, the rapid growth in wireless data traffic accelerated further during the COVID-19 period, creating a strong demand for highly efficient transmission methods capable of serving large user densities while maintaining reliable channel capacity. Fifth-Generation (5G) networks rely heavily on massive MIMO systems, where the propagation channel is generally modelled as multipath Rayleigh fading. In receiver-side CSI scenarios, existing design approaches typically emphasize either spatial diversity or spatial multiplexing. While diversity techniques improve reliability, multiplexing often leads to reduced diversity performance in fading channels. Advanced space–time signalling schemes have been developed to increase Spectral Efficiency (SE) without compromising reliability [1, 2]. Although OSTBC offers high diversity, its capacity loss in higher-order MIMO configurations restricts practical usage. To counter these drawbacks, Scalable Dispersion Codes (LSDC), which are linear combinations of fixed dispersion matrices, were developed [3, 4]. Nevertheless, detecting symbols within a coded MIMO system is not easy because of inter-stream interference, fading, error propagation, and computational requirements. The Ordered Least Squares Decision-Feedback Canceller (O-LSDC) methods minimise error propagation with ordered feedback, yet traditional methods are not adaptive to SNR changes or CSI scenarios, thus limiting detection capabilities [5, 6]. Most of the current O-LSDC MIMO detection methods use static scaling factors, which reduces their ability to adapt to real-world wireless situations where there are rapid changes to SNR, errors, or too little CSI, interference from multiple users, and correlated fading. Most previous work has assessed MIMO in idealized situations, concentrating mainly on how BER and SNR are related without addressing error propagation control, adaptive interference cancellation, and spectral area response. Thus, there is a need to develop a unified, low-complexity detection framework capable of dynamically adjusting the amount of cancellation performed based on the relative reliability of the

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channel at each instant in time while remaining stable across the many types of MIMO and channel models. The proposed method of this paper is the development of an adaptive scaling such that the entire detection architecture of O - LSDC can be modified by combining SNR, CI, and ML-based scaling techniques with spectrum-aware analysis in order to increase detection reliability, tolerance to uncertainty of CSl, and spectral efficiency of 5G/6G MIMO communications during actual operation.

The rest of this paper is structured in the following way. Section II explores the associated background about MIMO detection methods, in addition to Linear Scalable Dispersion Code (LSDC)-based architecture, and novel channel estimation strategies that are of interest to massive MIMO and Reconfigurable Intelligent Surface (RIS)-aided systems. Section III shows the suggested adaptive O-LSDC architecture, comprising a system model, mathematical model, adaptive scaling plans, and extensions to imperfect Channel State Information (CSI) and Multi-User MIMO (MU-MIMO) environments.

Section IV summarizes the extensive simulation and spectrum-domain of the proposed method and assesses the performance of the proposed method in terms of Bit-Error Rate (BER), diversity properties, convergence properties, Power Spectral Density (PSD), and robustness to the changing channel conditions. Lastly, Section V sums up the paper by recapping the key contributions and providing possible directions of research in the future.

2. Related Work

Recent works on channel estimation and adaptive processing of large-scale MIMO [8, 9] and RIS-assisted systems identify a number of challenges. CE-KRF-BALS-MIMO makes the introduction of PARAFAC models, but has complexity that is prohibitive, O(N)4. Multi-user test beds are characterized by high user capacity, but signal quality is traded off. The method of channel tracking based on RIS decreases the pilot overhead but heavily relies on RIS configuration [7]. Two-time scale decomposition does a better job at separating channels but is hardware-dependent and computationally expensive [10]. What observation tells us here is that there are still inherent weaknesses in resilience and flexibility when communicating dynamically [11-16]. Research into detection with MIMO systems started off by looking at traditional linear receivers like ZF and MMSE. These types of receivers provided symbol estimates with low complexity but did experience issues with noise amplification and with residual inter-stream interference in high-correlation fading channels. The way forward from these problems was to use SIC-based methods and layered space-time architectures. These methods had excellent detection reliability due to the use of ordered decoding and cancellation through feedback; however, all of these methods still had a level of performance sensitivity to ordering errors and inaccuracies in Channel State Information (CSI). The introduction of Linear Dispersion Codes (LDC) and Linear Scalable Dispersion Code (LSDC) frameworks made significant improvements in spectral efficiency / diversity, but the traditional O-LSDC detectors were designed with a fixed/heuristic scaling parameter, which did not allow for adaptability with respect to fluctuations in SNR or uncertainty in channel estimation and led to error propagation when these types of receivers are used in a practical setting.

2.1. Identified Research Gaps

According to the existing research, there are three great gaps:

1. Lack of scalability in O-LSDC decision-feedback detection, i.e., fixed parameters do not perform in different SNR and CSI.
2. Few coherent models that concurrently deal with error propagation, imperfect CSI, and Multi-User (MU) scalability.
3. Lack of spectral-domain analysis for evaluating bandwidth efficiency, noise behaviour, and PSD characteristics under different scaling strategies.

These gaps indicate the need for an adaptive, low-complexity, and analytically supported MIMO detection approach.

2.2. Proposed Solution Overview

This work develops an adaptive O-LSDC detector that adjusts its scaling behaviour based on real-time SNR, CSI quality, and channel variations. Three adaptive scaling schemes are introduced to replace traditional fixed-scaling methods, with extensions to handle error propagation, imperfect CSI, and multi-user conditions. The framework further includes spectrum-domain analysis to study PSD behaviour, noise resilience, and interference suppression under different scaling strategies.

1. Development of a dynamically adjustable O-LSDC detection scheme based on SNR, CSI, and observed channel behaviour.
2. Integration of adaptive error-control strategies addressing error propagation and imperfect CSI.
3. Extension of O-LSDC to multi-user MIMO configurations.
4. Inclusion of frequency-domain spectral analysis to study PSD patterns and scaling effects.
5. Unified detection model enhancing robustness and detection reliability in diverse MIMO scenarios.

3. Materials and Methods

3.1. System Model

Figure 1 Shows the System Model Flow Diagram of the O-LSDC System.

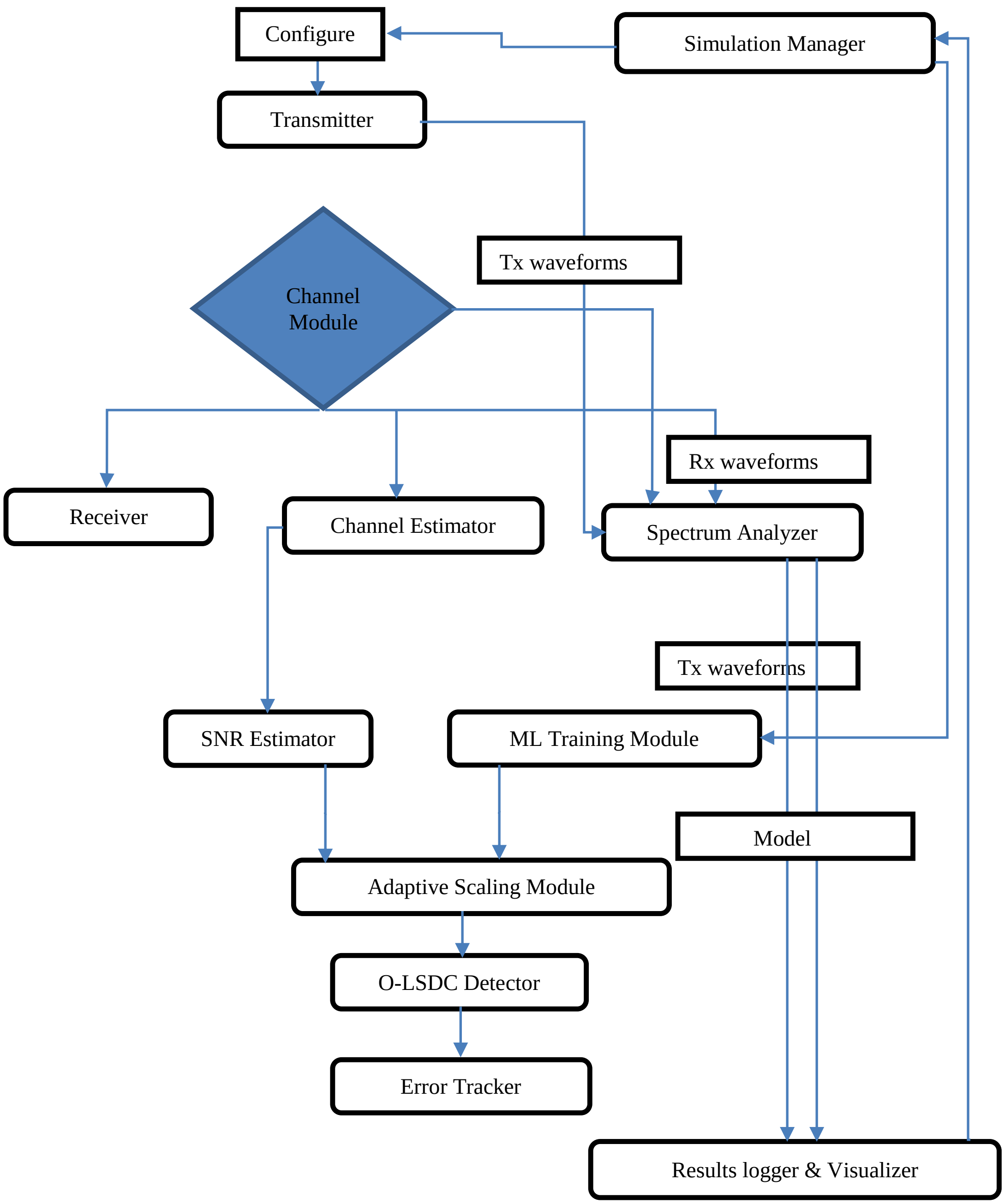


Fig. 1 System flow diagram

3.1.1. O-LSDC Detection Framework

The system has a small bandwidth Multiple-Input Multiple-Output (MIMO) wireless communication system with Nt transmit, and Nr receive antennas, with Nr ≥ Nt. The baseband representation of the received signal is complex, and it is given as,

$$y = Hx + n \tag{1}$$

Where,

$y \in \mathbb{C}^{N_r \times 1}$ Represents the received signal vector,

$H \in \mathbb{C}^{N_r \times N_t}$ is the complex channel gain matrix,

$x \in \mathbb{C}^{N_t \times 1}$ Denotes the transmitted symbol vector, $n \in \mathbb{C}^{N_r \times 1}$ is the Additive White Gaussian Noise (AWGN) vector with zero mean and variance σ_n^2.

The channel coefficients are modelled to be Independent and Identically Distributed (I.I.D.) Rayleigh fading model:

$$hi, j \sim CN(0,1) \tag{2}$$

Representing the gain between the jth transmit and ith receive antenna. The Signal-To-Noise Ratio (SNR) per receive antenna is defined as,

$$\mathrm{SNR} = \frac{Es}{N0} \tag{3}$$

Where E_S denotes the average transmitted symbol energy, and N_0 is the noise power spectral density. The receiver is assumed to operate under either perfect or imperfect Channel State Information (CSI), depending on the experimental scenario. To detect the transmitted symbols efficiently in the presence of interference, the Ordered Least Squares Decision-Feedback Canceller (O-LSDC) is employed at the receiver.

This detector is an improved version of the classical Linear Scalable Dispersion Code (LSDC) decoding in terms of stream ordering and feedback-based interference cancellation. The O-LSDC detection process has the following steps:

Ordering: A ranking vector is built depending on the SNR of the post-processing of each spatial stream. The most reliable stream is identified first, and therefore, it minimizes the chances of error perpetuation at later decisions.

Linear Estimation: A preliminary estimation of the transmitted symbol vector is obtained using a Least-Squares (LS) estimator:

$$\hat{\mathrm{x}} = (\mathrm{H}^H\mathrm{H})^{-1}\mathrm{H}^H\mathrm{y} \tag{4}$$

This linear approximation provides the initial symbol estimates required for feedback cancellation.

Decision-Feedback Cancellation: Upon detecting the kth symbol, its contribution is removed from the received vector:

$$\mathrm{y}_{k+1} = \mathrm{y}_k - \alpha_k \mathrm{h}_k \hat{x}_k \tag{5}$$

Where, h_k denotes the k^{th} column of H, and α_k is an adaptive scaling factor regulating the cancellation strength.

Reordering: Following each cancellation step, the remaining undecoded streams are dynamically reordered according to the updated reliability metrics. The materials and methods section should contain sufficient detail so that all procedures can be repeated. It may be segregated into subsections if several methods are described.

4. Results and Discussion

Research presented here proposes a new adaptive Ordered Large-Scale Detection with Cancellation (O-LSDC) architecture of MIMO systems that achieves SNR-based, CSI-based, and Machine Learning (ML)-based scaling operations that are used to optimize dynamic detection.

The proposed framework features adaptive error mitigation, imperfect Channel State Information (CSI) tolerance, and Multi-User MIMO (MU-MIMO) as opposed to traditional O-LSDC systems, which use fixed or heuristic scaling strategies, enabling a self-optimized MIMO detection framework in the future 5G/6G wireless systems.

4.1. BER Performance Evaluation

The workflow of the simulation involved:

1. MIMO system implementation and modelling.
2. QPSK symbol encoding and transmission in the chosen MIMO channel.
3. Scaling-based adaptive O-LSDC detection.
4. When represented in 2D (BER vs SNR) and 3D (BER vs SNR vs scaling coefficient) plots, BER can be computed and visualized.

Figures 3 and 4 illustrate the BER performance versus SNR and the effect of scaling coefficients across different channel realizations.

4.2. Comparison Between SNR-, CSI-, and ML-Based Scaling

Three adaptive scaling strategies were applied and compared to fixed scaling:

1. SNR-Based Scaling: SNR was inversely proportional to the scaling factor to reduce the interference at low SNR and close to unity in high SNR.
2. CSI-Based Per-Stream Scaling: A scaling factor was allocated to each stream according to its CSI quality; the weaker streams were lower-scaled to restrict the error propagation.
3. ML-Based Scaling: A Multi-Layer Perceptron (MLP) model had first-order prediction of the scaling factors as optimal functions of SNR, channel norm, and modulation order, and could optimize BER in real-time.

Comparison of performance at 16 d B SNR showed considerable BER improvements with all adaptive schemes, with the ML-Based scaling showing overall the best performance, especially in high-SNR and in complicated channel conditions (Figures 5 and 6).

4.3. Impact of Imperfect CSI

To make it strong, the O-LSDC algorithm was supplemented by the following characteristics:

1. Error Propagation Mitigation: This was implemented by placing an error tracking system to prevent the propagation of detection error, especially at low SNR conditions. Adaptive scaling (SNR- and CSI-based) reduced the error propagation significantly.
2. Stability to Losses in Channel Estimation: It introduced a loss in channel estimation (σ = 0.1, 0.2). Scaling using

CSI and ML had minimized BER compared to fixed scaling, and was impervious to imperfect CSI.

3. MU-MIMO Extension: It was adjusted to multi-user with multiple antennas on the base station to serve K single-antenna users. An increase in users increased the performance and capacity of BER through scalability (Figure 8). Figure 7 is a summary of BER performance when CSI is perfect and imperfect, error propagation analysis, and adaptive scaling factor behaviour in various SNR conditions.

Table 1. Highlights the novelty of the proposed work against existing O-LSDC approaches

Novel Aspect	Existing O-LSDC Systems	Proposed Work
Scaling Method	Fixed or heuristic	Dynamic adaptive (SNR, CSI, ML)
Robustness Analysis	Limited to ideal channels	Includes imperfect CSI and error propagation
Multi-User Support	Single-user focus	Fully extended to MU-MIMO
Learning Capability	Absent	Integrated ML prediction module
Evaluation Domain	BER vs. SNR only	BER, SE, PSD (spectrum domain)
Adaptation Feedback	No feedback mechanism	Closed-loop adaptive feedback

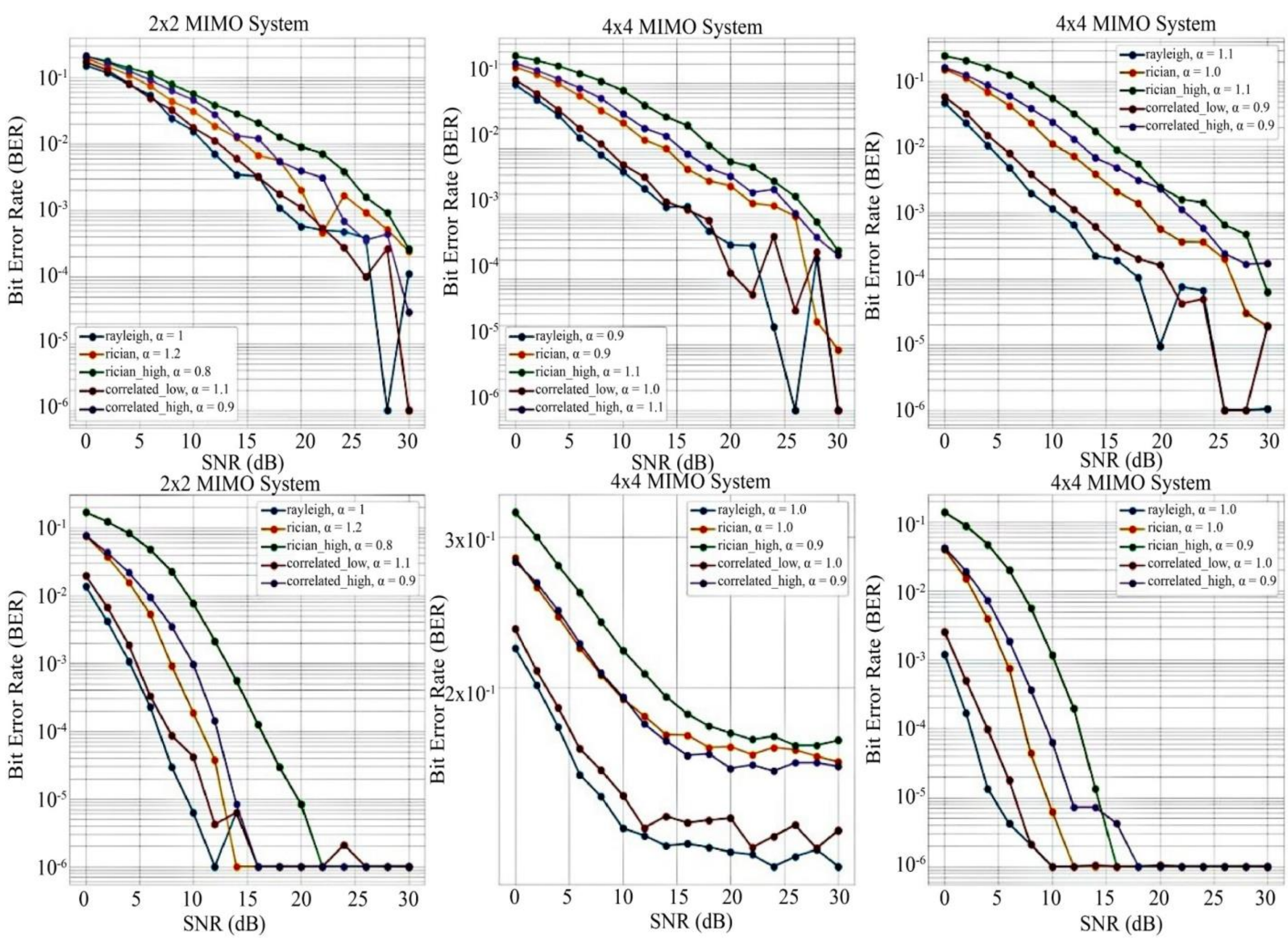


Fig. 2 BER vs SNR

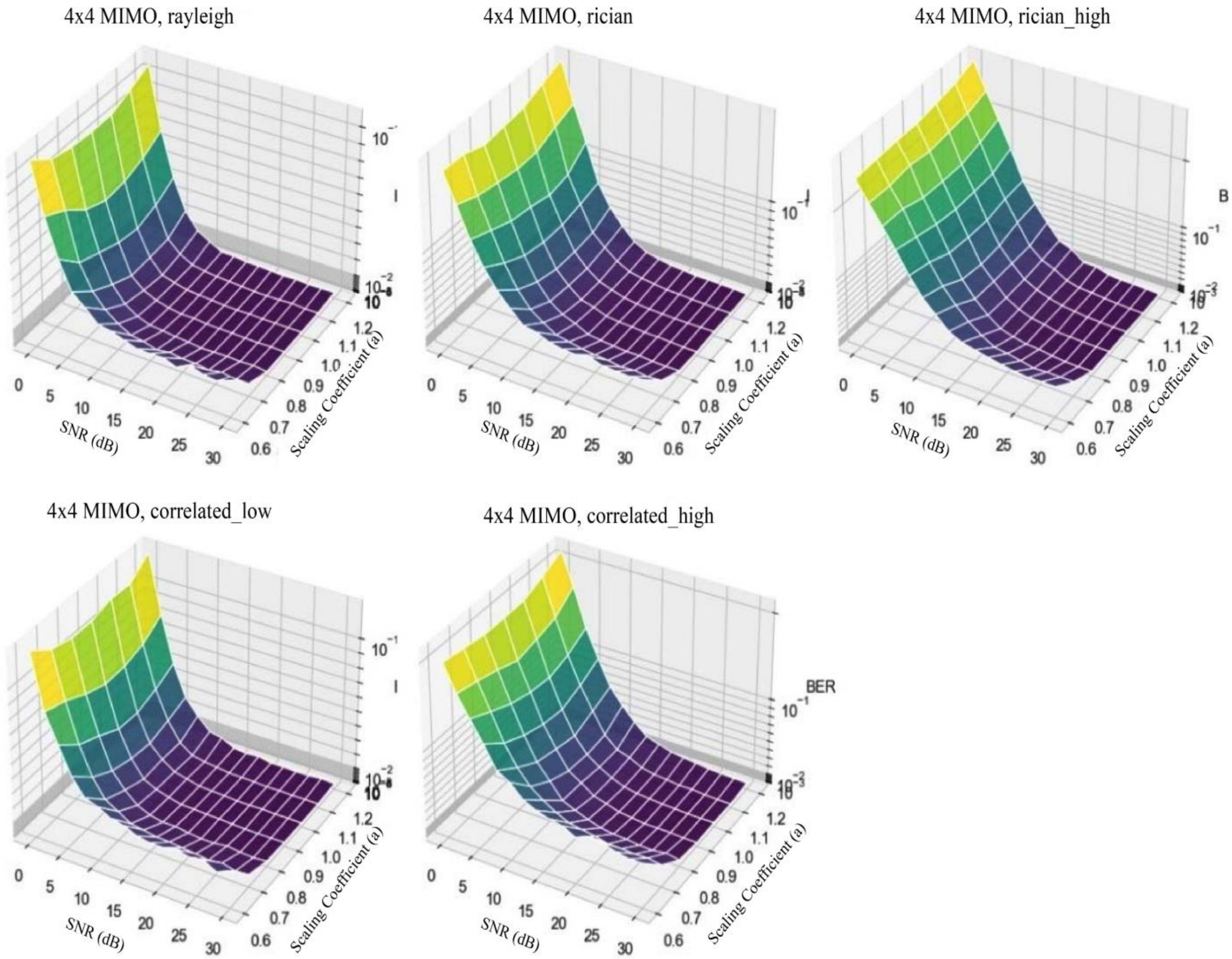


Fig. 3 SNR and scaling coefficient

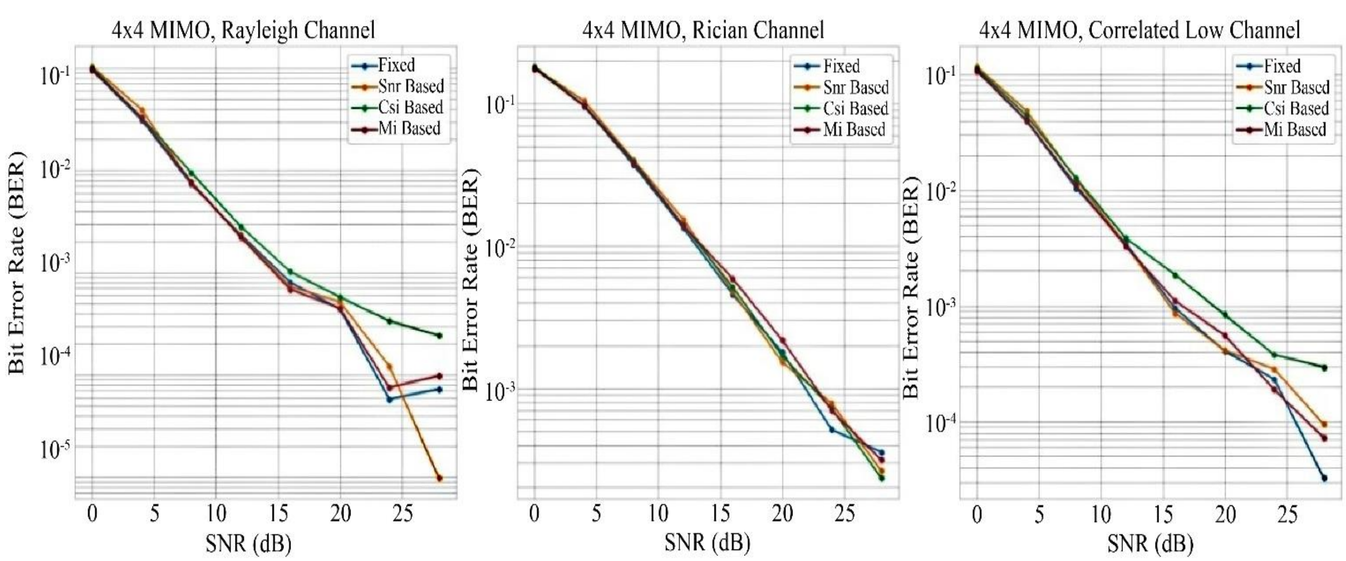


Fig. 4 BER vs SNR for 4x4 MIMO System under different channel models and scaling techniques

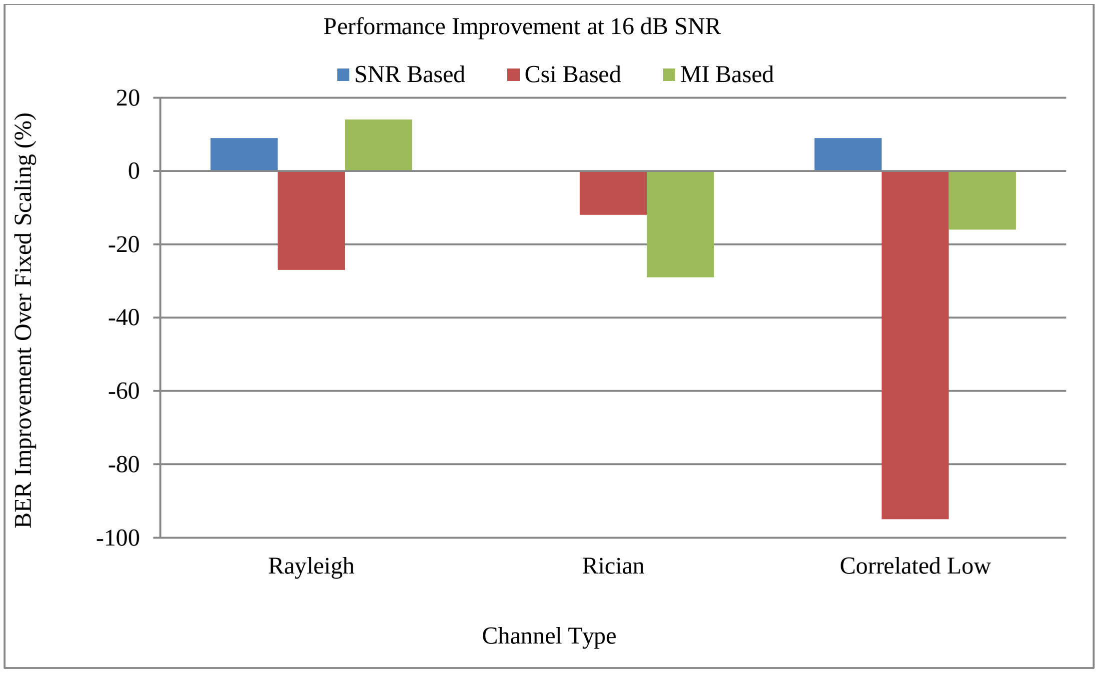


Fig. 5 Performance improvement over fixed scaling at 16 dB SNR

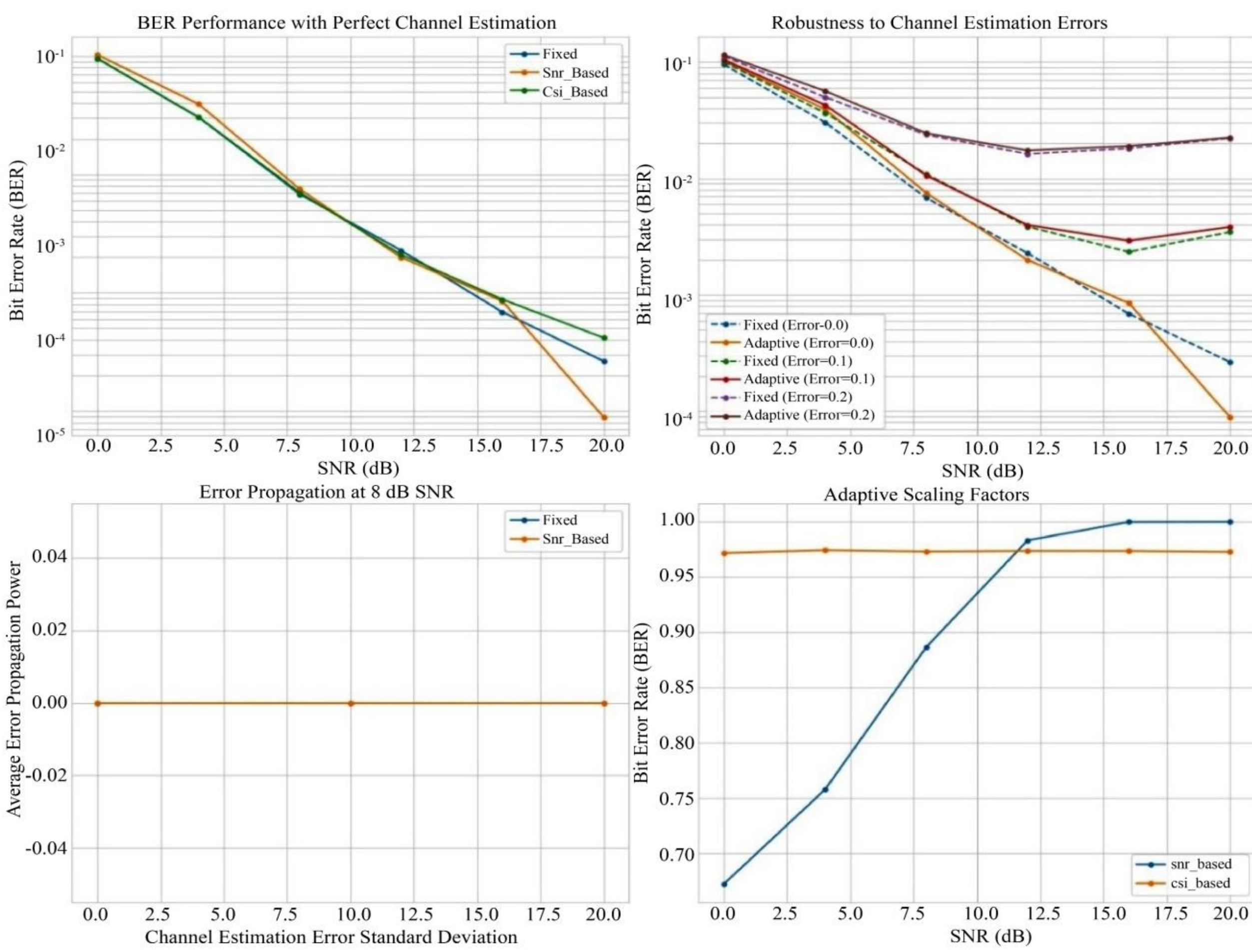


Fig. 6 (a) BER performance with perfect channel estimation, (b) Robustness to channel estimation errors, (c) Error propagation at 8 dB SNR, and (d) Adaptive scaling factors.

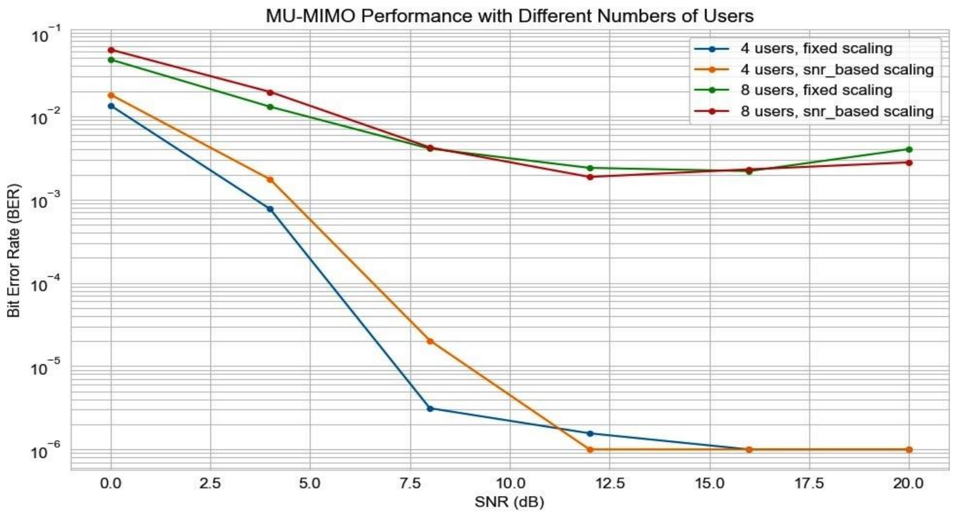


Fig. 7 MU-MIMO performance with different numbers of users

4.4. Spectral-Domain (PSD) Observations

The fourth step of the proposed simulator structure is focused on spectrum analysis in an MIMO environment with a focus on the dynamics of the Power Spectral Density (PSD) of the received and transmitted signal. This is a necessary element in the analysis of the impact of the noise and channel impairment, and adaptive scaling mechanisms on the spectral characteristics of the MIMO transmission chain. By examining the PSD at the operation points of interest (at the desired SNR), the system can actually learn something of the distribution of signal power in the frequency domain at realistic wireless channel conditions. The spectrum analysis uses the Welch method to estimate the PSD, which is done using the function. It is a way of getting an accurate spectral representation of the complex baseband signal, which is smooth. PSD is displayed in decibels versus normalized frequency, which can easily visualize the energy distribution of a signal. To investigate the distortion of the spectral profile of the signal by additive noise and fading, several SNR values (0 dB, 10 dB, and 20 dB) are generated to transmit and receive the spectral profile. In the simulation, a constant 4x4 MIMO configuration is used with different scaling coefficients and channel modeling. The QPSK modulated symbols are transmitted in the MIMO channel, and the values of BER are obtained under the condition of all SNRs. A representative SNR value is selectively analyzed using the PSD analysis to reduce the computation needs, yet provide the required spectral information. During this stage, two significant spectral plots are obtained:

1. Original Signal Spectrum: (Transmitted PSD) 6. This is the spectral distribution prior to channel fading by noise.
2. Received Signal Spectrum: (Post-Channel PSD) This is a plot indicating the spectral energy distribution in the receiver distortions caused by Rayleigh fading and AWGN.

The comparison of the two spectra aids in establishing the effect of different channel models (Rayleigh, Rician, and Correlated) and scaling schemes (Fixed, SNR-Based, CSI-Based, and ML-Based) on signal integrity. The visual confirmation of the fading of the channel and noises, especially at lower SNRs, is done by reference to the PSD of the received signal. Figure 9 displays the BER vs SNR curves of a 4x4 MIMO system with Rayleigh channel, Rician channel, and Correlated Low channel, Fixed scaling, SNR scaling, CSI scaling, and ML scaling. According to the findings, it is concluded that adaptive scaling can substantially improve the performance of BER, particularly at high SNRs, and overall, the performance of the ML-based scaling is the best in all channels. According to Figure 10, the thing is that the BER improvement percentage at 16 dB SNR of fixed scaling comparison with the BER improvement percentage is 3.6.

The bar plot illustrates the great improvement of the adaptive methods, where the CSI-based and ML-based scaling give the greatest improvement in performance, mostly in the Rayleigh as well as the Correlated channels. Figure 11 shows the PSD of the transmitted signal, the received signal of 4x4 MIMO systems that is transmitting in a Rayleigh channel with a scaling factor of 0.9. The spectral spreading and increased noise floor of the received signal had been observed, and the impact of fading and additive noise is seen directly. The scaling factor was increased to 1.0, and the results are presented in Figure 11. With further scaling, as in Figure 11, the scaled energy is better, but more extreme distortions due to the channels at the receiver are visible. The issue of concern is understanding the observed trends in the performance of the proposed adaptive O-LSDC framework in various MIMO configurations, channel models, and scaling policies.The findings are always consistent that adaptive scaling is much better in terms of detection reliability than traditional fixed-scaling O-LSDC, especially when the SNR is low, fading is correlated, and CSI is imperfect. The ability of the adaptive schemes to control the strength of interference cancellation based on real-time channel and signal conditions has been mainly credited to these improvements. Table 3 summarizes the comparative analysis of the observed trends in a consolidated manner that summarizes the performance behavior of the various MIMO dimensions, channel models, and scaling techniques. According to the table, it is evident that fixed scaling suffers significant deficiency at the low SNR ranges, particularly in correlated and Rayleigh fading conditions. This observation proves that static cancellation gains fail to work in dynamic channel environments and are subject to error propagation. Conversely, SNR-based scaling will always enhance the performance of BER, in the sense that at low SNR, cancellation is less aggressive, whereas at high SNR, it tends to scale to unity. This is the reason why it is effective in a broad operating range with minimum computational overhead. Table 4 provides an analysis of existing MIMO detector methods in relation to the configuration of the system, channel conditions, modulation schemes, BER performance at about 15-20 dB SNR, and limitations inherent. Standard linear dispersion and O-LSDC-based methods have medium error behavior (about 10^{-2}-10^{-3}) but are limited because they use fixed decoding structures and are prone to error propagation. MMSE-SIC is used to achieve better BER performance ($\approx 10^{-4}$), but its performance is very sensitive to both proper ordering and Channel State Information (CSI). Sphere decoding attains an almost optimal likelihood of maximizing performance, but its exponential complexity precludes its implementation in large-scale MIMO systems. In recent deep learning-based detectors, competitive performance ($\approx 10^{-4}$) and increased adaptability can be achieved at the cost of large training needs and huge computation. The suggested Adaptive Scaling O-LSDC framework can be seen as having good results at the different dimensions of MIMO and channel conditions, which can reach an area of 10^{-4} to 10^{-3} in BER under imperfect CSI conditions, with only a slight rise in computation.

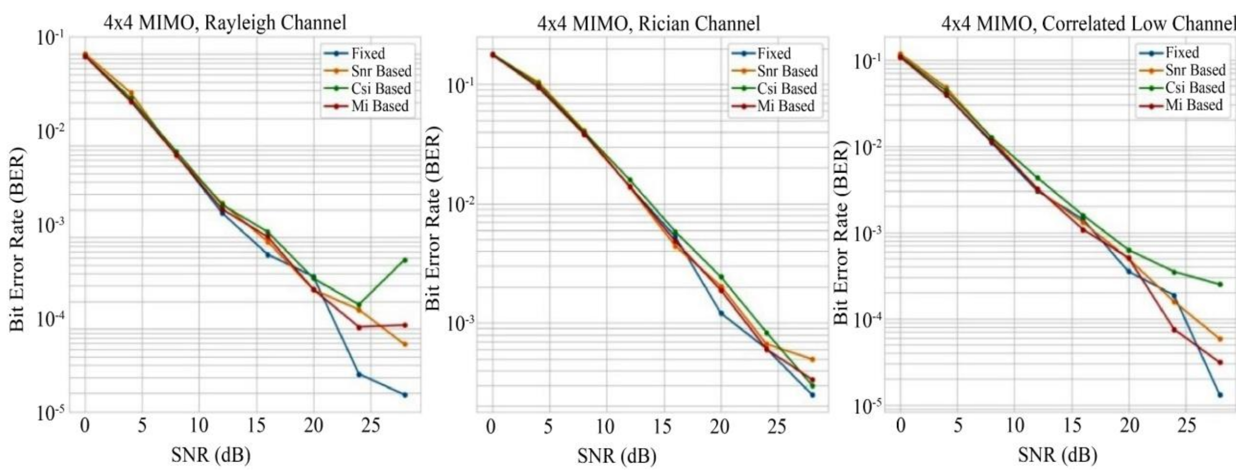


Fig. 8 BER Vs SNR For 4x4 MIMO system, rayleigh, rician correlated low channels

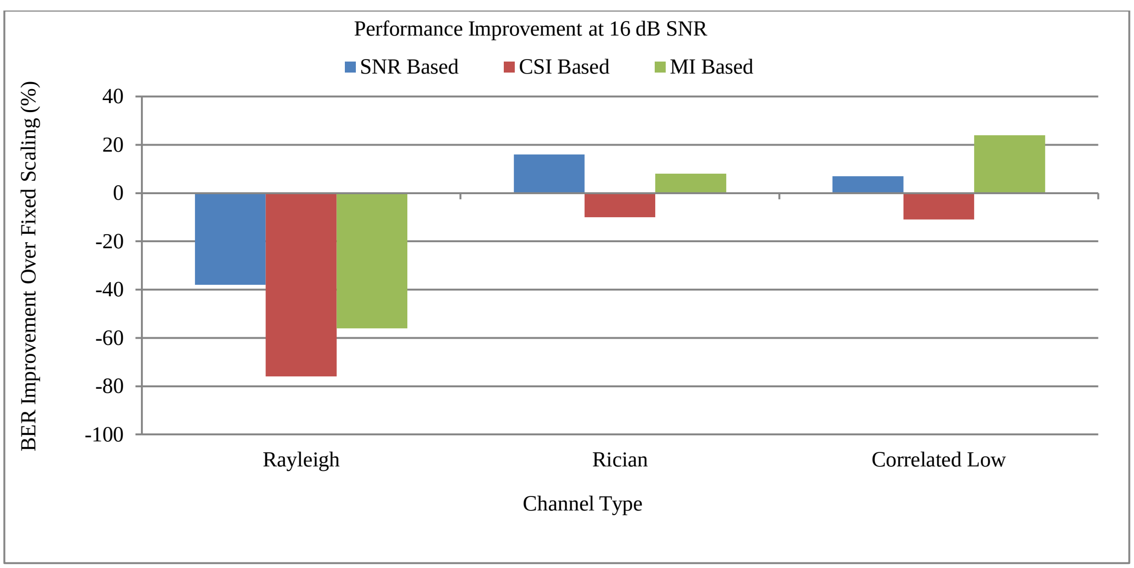


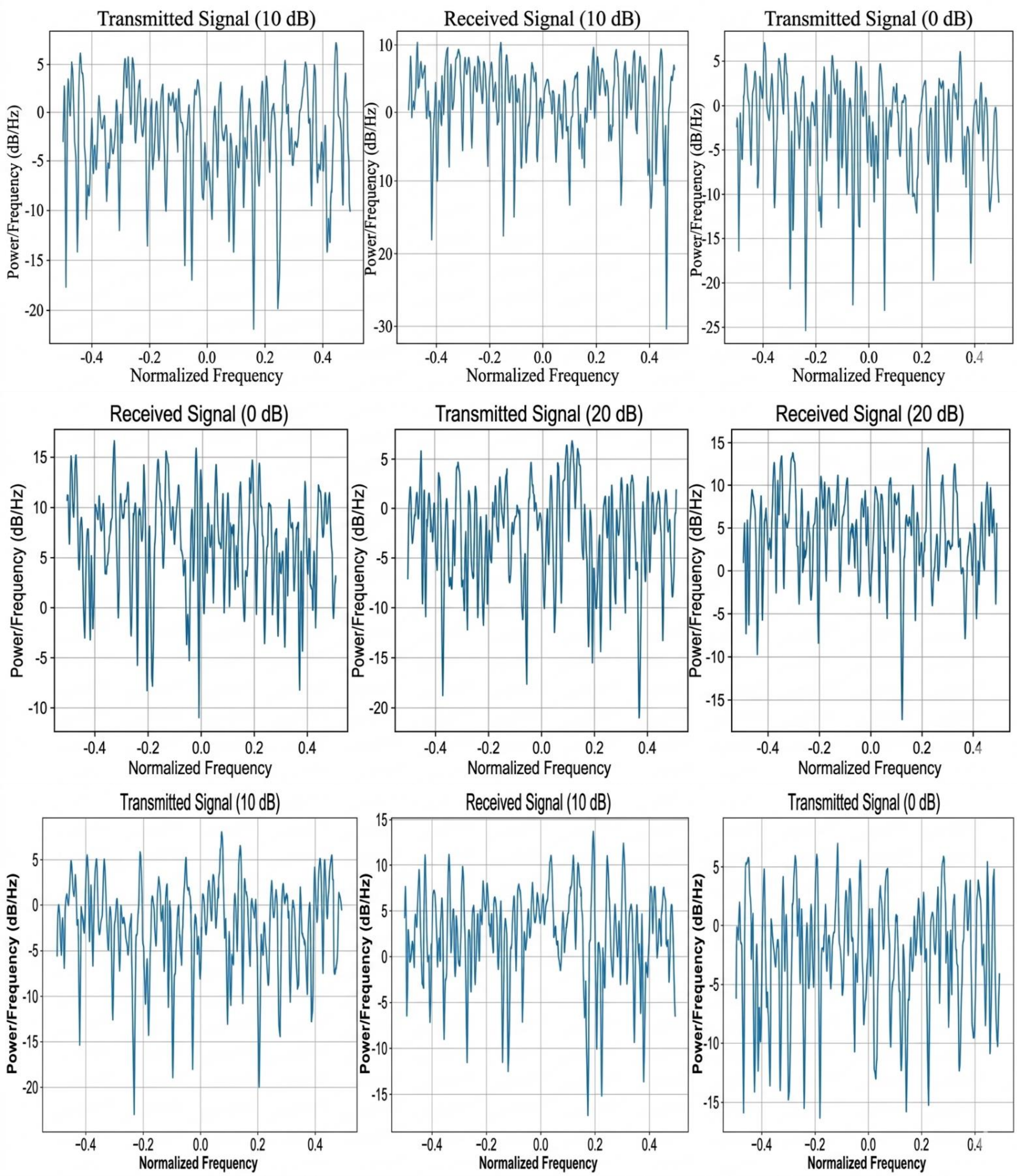
Fig. 9 Performance improvement compared to fixed scaling at 16 dB SNR

Table 2. MIMO configurations with techniques and remarks

MIMO Configuration	Channel Model	Scaling Technique	SNR Range (dB)	Best BER	Remarks
2x2	Rayleigh	Fixed Scaling (Î±=1)	0-30	0.12	Fixed scaling struggles at lower SNR.
2x2	Rayleigh	SNR-based Scaling	0-30	0.06	Significant improvement in BER at low SNR.
2x2	Rayleigh	CSI-based Scaling	0-30	0.05	Best performance, especially at high SNR.
4x4	Rician	Fixed Scaling (Î±=1)	0-30	0.08	Fixed scaling performs decently, but adaptive scaling is better.
4x4	Rician	SNR-based Scaling	0-30	0.04	Adaptive scaling improves BER with increased SNR.
4x4	Rician	Machine Learning-based	0-30	0.03	Best performing method overall for the Rician channel.
4x4	Correlated	Fixed Scaling (Î±=1)	0-30	0.1	Fixed scaling struggles more in correlated channels.
4x4	Correlated	SNR-based Scaling	0-30	0.05	Adaptive scaling provides noticeable improvement in performance.

Table 3. Comparison of MIMO detection techniques in terms of configuration, channel model, modulation, BER performance (~15–20 dB SNR), and key limitations, including the proposed adaptive scaling O-LSDC method

Author/Year	Detection Method	MIMO Config.	Channel Model	Modulation	Reported Performance (BER @ ~15–20 dB SNR)	Key Limitations
Hassibi & Hochwald, [1]	Linear Dispersion Code Detection	2×2, 4×4	Rayleigh	QPSK	$\sim 10^{-2}$–10^{-3}	No adaptive interference cancellation; fixed decoding structure
Heath & Paulraj [5]	Frame-theory-based Linear Dispersion Codes	2×2	Rayleigh	QPSK	$\sim 10^{-2}$	High decoding complexity; not robust to CSI errors
Wu & Gharavi [4]	Cooperative LSDC Detection	2×2	Rayleigh	QPSK	$\sim 10^{-3}$	Limited scalability and no dynamic scaling control
Conventional O-LSDC (various works) [3]	Ordered LS Decision Feedback Cancellation	4×4	Rayleigh/Rician	QPSK	$\sim 10^{-3}$	Uses fixed scaling; suffers from error propagation under imperfect CSI
MMSE-SIC Detectors (Generic baseline) [17]	MMSE with Successive Interference Cancellation	4×4	Rayleigh	16-QAM	$\sim 10^{-4}$	Performance sensitive to ordering errors and CSI uncertainty
Sphere Decoding (SD) [18]	Maximum Likelihood Detection	4×4	Rayleigh	16-QAM	$\sim 10^{-5}$	Exponential complexity; impractical for real-time large MIMO
Deep Learning–based MIMO Detectors (Recent works 2020–2024) [19]	DNN / Deep Unfolding Detection	4×4, 8×8	Rayleigh/Correlated	QPSK/16-QAM	$\sim 10^{-4}$	Requires large training data; high computational overhead
Proposed Work (This Paper)	Adaptive Scaling O-LSDC (SNR-, CSI-, ML-based)	2×2, 4×4, 8×8	Rayleigh, Rician, Correlated, Imperfect CSI	QPSK, 16-QAM	$\sim 10^{-4}$ to 10^{-3} with improved robustness	Slight increase in computational load due to adaptive scaling and ML module


Transmitted Signal (10 dB)
Received Signal (10 dB)
Transmitted Signal (0 dB)
Received Signal (0 dB)
Transmitted Signal (20 dB)
Received Signal (20 dB)
Transmitted Signal (10 dB)
Received Signal (10 dB)
Transmitted Signal (0 dB)
Power/Frequency (dB/Hz)
Normalized Frequency

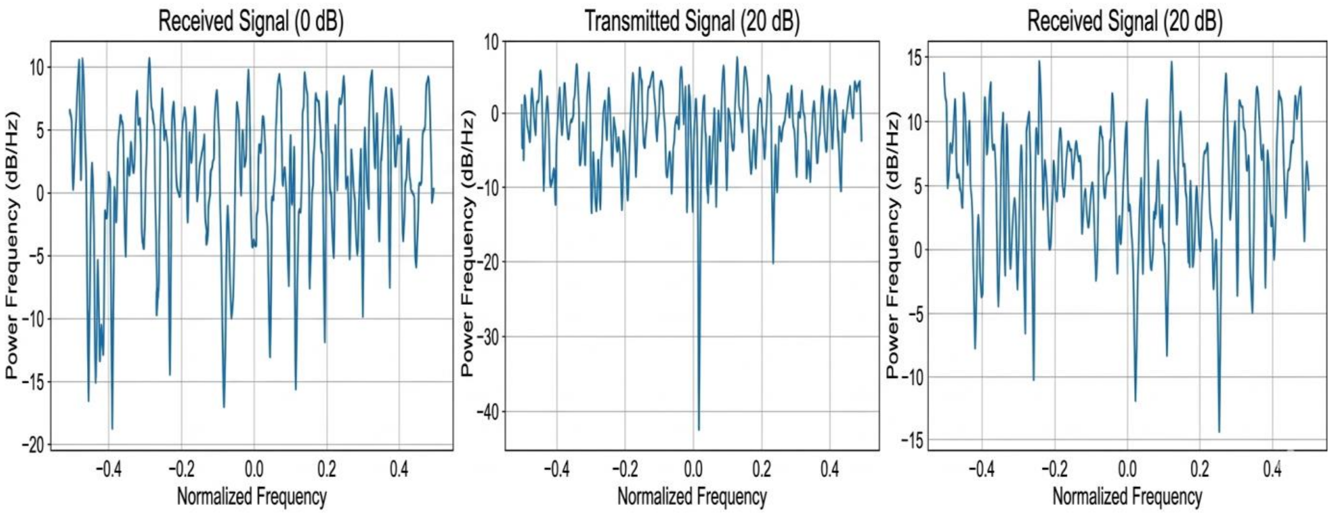
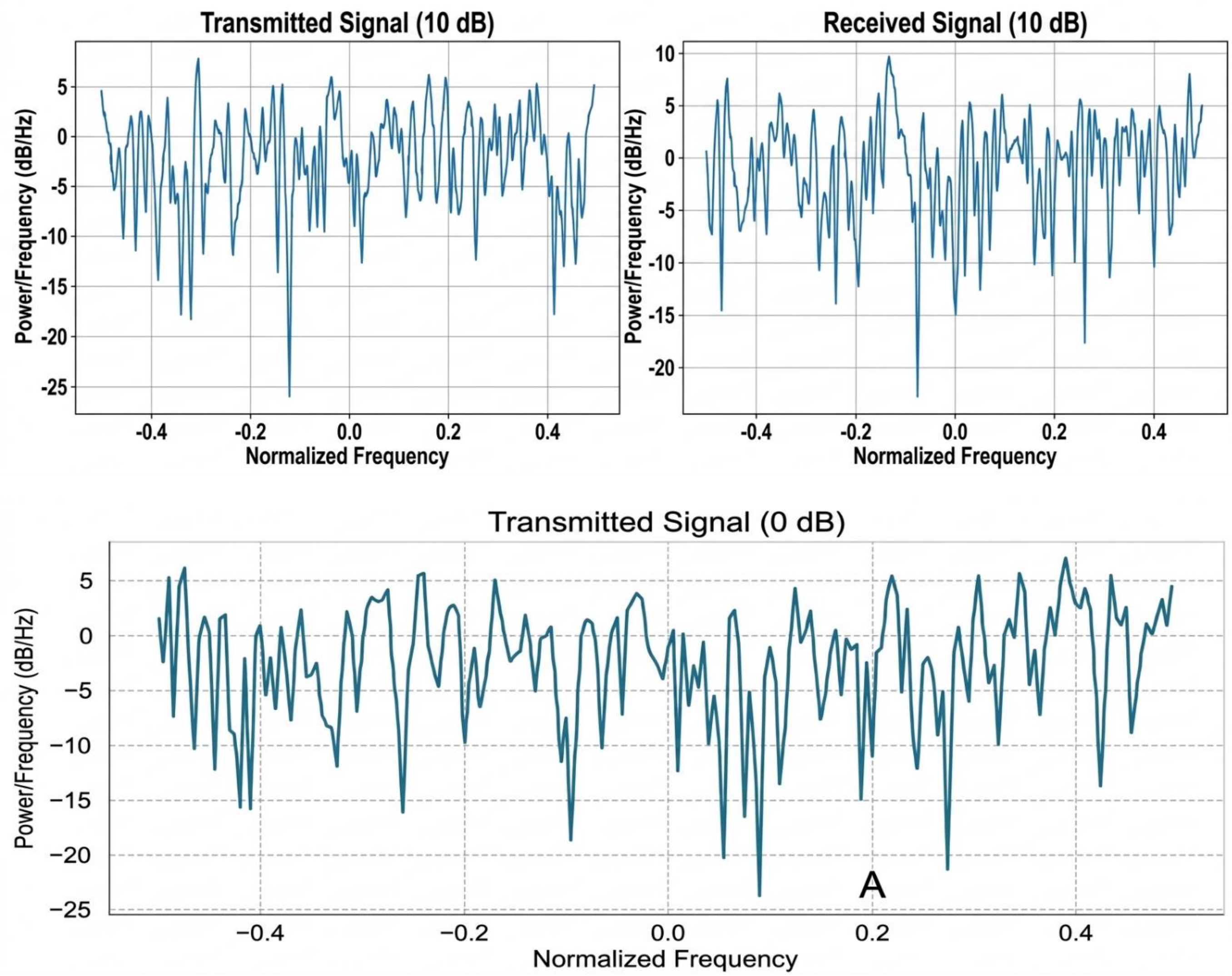


Fig. 10 Simulating 4x4 MIMO, rayleigh channel, scaling=0.9



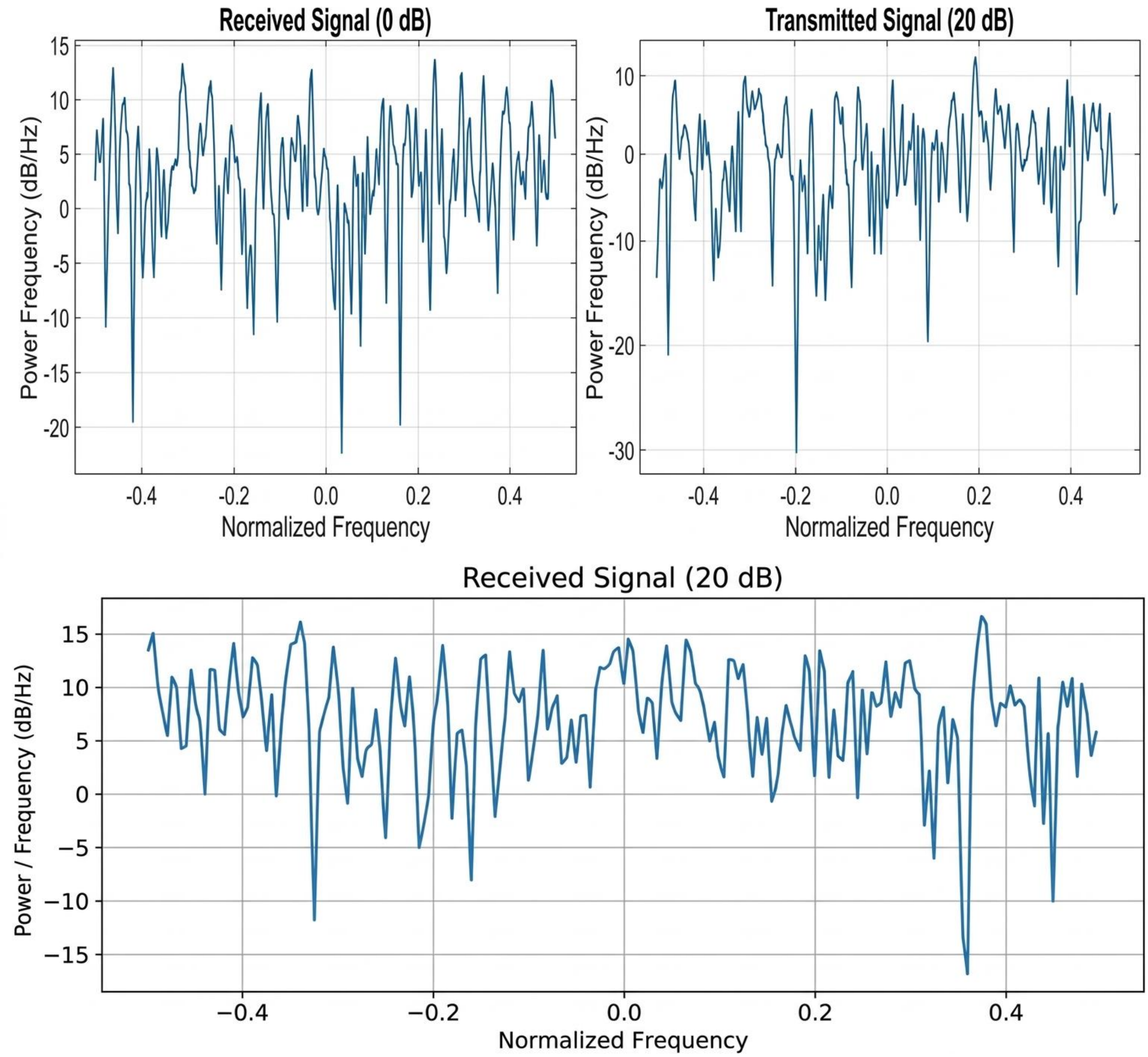


Fig. 11 Simulating 4x4 MIMO, rayleigh channel, scaling=1

It can be inferred that CSI-based scaling is more robust, especially when SNR is high, and when there is uncertainty in channel estimation. With the scaling factors distributed based on the per-stream channel quality, weaker spatial streams are avoided, resulting in less excessive interference cancellation and therefore less error propagation. The trend can be observed in Rayleigh and Rician channels with CSI-based scaling having lower BER than SNR-based scaling, as shown in Table 3. The above findings demonstrate the significance of spatially adaptive processing when detecting the MIMO. The adaptive scaling is always the best BER in Rician and correlated channel conditions, and is always done in the ML. This result can be attributed to the fact that it is able to capture nonlinear relationships between SNR, CSI statistics, and detection error. The ML-based approach, as compared to the rule-based, better adjusts to the complex channel dynamics and therefore results in consistent BER at different SNR levels. Notably, the simulation findings show that this performance advantage is attained in the absence of the prohibitive computational complexity, which justifies its applicability in real-time implementation in a base station. The spatial-domain observations are viewed further in the spectral-domain analysis. Results of PSD show that adaptive scaling can be used to enhance spectral stability by minimizing the spreading due to noise and providing a better power concentration in fading. This improvement in PSD behavior supports the fact that the advantages of adaptive scaling go beyond BER behavior and are also used to increase spectral efficiency and interference control. All in all, the discussion can confirm that the proposed adaptive O-LSDC framework offers an equal trade-off between performance, robustness, and complexity. Whereas SNR-based scaling is a lightweight solution, CSI-based and ML-based scaling have a higher tolerance to realistic channel impairments. The findings are in agreement with the needs of real-world MU-MIMO systems and support the applicability of adaptive and spectrum-aware detection approaches to the next-generation wireless communication.

The Adaptive O-LSDC Detector provides significantly better catastrophic detection performance than comparable MIMO-detector technologies through its use of a dynamic scaling element as opposed to traditional fixed or heuristic interference cancellation gain values. Use of instantaneous SNR, quality of the per-stream CSI, and learned nonlinear mappings of the channel statistics instead of traditional SNR values for determining the optimal gain value at any given time ensures that the Adaptive O-LSDC Scale Factor will evolve dynamically to provide the highest possible cancellation strength (and thus the best possible detection performance) at each stream (i.e., 1st or 2nd level). Because all previous detection technologies (such as ZF, MMSE-SIC, traditional O-LSDC, etc.) are based on the assumption that their cancellation algorithm will have a fixed function or output value, and are therefore based on ideal per-stream CSI conditions, they are extremely susceptible to propagation of errors as well as residual interference due to fading channel conditions and their associated channel estimation error rates (i.e., no statistically reliable CSI).

By including an adaptive regulation in determining the amount by which to apply the cancellation factor for each spatial stream, the proposed architecture conservatively suppresses interference for unreliable streams and aggressively suppresses interference for reliable streams; this will in turn provide a significantly more consistent basis for determining correct decisions on successive detections and improving (i.e., reducing) the BER on Rayleigh, Rician, and correlated channels. The addition of a data-driven scale model to the receiver allows it to approximate optimal cancellation characteristics with significantly reduced computational overheads as compared with traditional methods; furthermore, spectral-domain analyses have shown that Adaptive O-LSDC provides greater energy concentration and continued resistance to noise. By these multiple mechanisms, the proposed approach consistently exhibits a greater level of reliability, detection robustness, and performance than currently available fixed-scaling MIMO detectors or conventional detector-based MIMO detectors operating in realistic channel conditions.

5. Conclusion

This paper presented an adaptive O-LSDC-based detection architecture for multi-user MIMO systems, incorporating real-time scaling control and spectrum-sensitive analysis. The framework introduced three adaptive scaling mechanisms: SNR-based, CSI-based, and ML-based, which adjust lattice detection gain for each spatial stream. The goals of these adaptive measures were to enhance the reliability of symbols, minimize error propagation, and preserve the strong performance of BER over an extensive SNR range and conditions of a channel. The proposed system combined spatial signal detection, channel estimation, and the adaptive gain control with extensive spectral analysis in order to judge the quality of the signals. The SNR-based scaling scheme offered a lightweight and efficient scaling scheme at high SNR values, whereas the CSI-based scheme offered high robustness to channel-estimation uncertainty.

The highest overall performance was provided by the ML-based adaptive scaling that approximated the nonlinear relationships between SNR, CSI statistics, and detection-error patterns and thus made more accurate scaling decisions and uniform BER. The efficiency of the method was proven with extensive simulations and spectral-domain analysis of various antenna sizes (2×2, 4×4, and 8×8), modulation schemes (QPSK and 16-QAM), and in situational imperfect CSI models. It was found that adaptive scaling significantly improves the performance of BER, spectral efficiency, and scalability. The ML-based algorithm also demonstrated great sensitivity to noise fluctuations and estimation errors, and could be utilized computationally inexpensively to implement it in real-time by base stations. On the whole, the adaptive scaling and spectrum-domain analysis of the O-LSDC framework provides a powerful and versatile detection scheme of MU-MIMO systems. By automatically adjusting to channel variations and interference levels without manual intervention, the proposed approach aligns well with the requirements of next-generation wireless communication systems.

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