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Implementation and Evaluation of a Conjugate Gradient (CG) Detector for 5G/6G-Like MIMO Scenarios Using Sionna

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Abstract

Massive multiple-input multiple-output (MIMO) systems are a cornerstone of 5G and emerging 6G wireless networks due to their ability to provide high spectral efficiency and improved reliability. However, signal detection in large-scale MIMO systems remains a major challenge because of the high computational complexity associated with conventional linear detectors. In this paper, we investigate the Conjugate Gradient (CG) algorithm as a low-complexity iterative detection technique for massive MIMO systems. The MIMO detection problem is formulated as a system of linear equations and solved using the CG method implemented within the Sionna simulation framework. The convergence behavior and bit error rate (BER) performance of the proposed detector are analyzed under different signal-to-noise ratio (SNR) levels and spatial correlation scenarios. Simulation results show that the CG-based detector achieves near-optimal BER performance while significantly reducing computational complexity compared to classical linear detectors such as the linear minimum mean square error (LMMSE) detector. These results demonstrate that CG-based detection is a promising and efficient solution for practical large-scale MIMO deployments.

Keywords: Massive MIMO; Conjugate Gradient; Signal Detection; 5G and 6G; Bit Error Rate.

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1. Introduction

The growth of data-intensive applications, IoT, and autonomous systems demands higher throughput and lower latency in wireless communications. Massive MIMO enhances spectral efficiency, robustness, and spatial multiplexing but makes signal detection challenging under interference and spatial correlation. Conventional detectors like ZF and LMMSE are reliable but computationally expensive. The Conjugate Gradient (CG) algorithm offers a low-complexity iterative alternative, approximating LMMSE performance efficiently. In this paper, we implement CG-based MIMO detection using Sionna and analyze its BER, convergence, and computational complexity under various SNR and channel conditions.

2. Related Work

Several linear detection techniques have been proposed for MIMO systems to address the challenges of high-dimensional signal detection. Among the most common are the Zero-Forcing (ZF) and Linear Minimum Mean Square Error (LMMSE) detectors. The ZF detector aims to completely eliminate interference by inverting the channel matrix. Although it provides interference-free estimation, it amplifies noise, especially in ill-conditioned channels [1, 3]. The LMMSE detector improves performance in noisy environments by introducing a regularization term to balance noise enhancement and interference suppression, but this comes at the cost of higher computational complexity [1, 3].

To reduce the complexity of linear detection, iterative methods have been proposed. In particular, the Conjugate Gradient (CG) algorithm has gained attention as a low-complexity alternative that approximates LMMSE performance without directly inverting the channel matrix [4–6].

CG-based detectors have been shown to achieve near-optimal performance while significantly reducing computational overhead, making them suitable for large-scale and massive MIMO systems [4–6].

Recent works have also focused on realistic implementation and evaluation of CG-based detection. Frameworks such as Sionna facilitate accurate simulations of massive MIMO systems, including channel effects, spatial correlation, and varying SNR conditions [7, 9, 10]. These platforms allow researchers to evaluate the convergence behavior, bit error rate (BER), and computational complexity of CG-based detectors in scenarios that closely resemble practical 5G and 6G deployments.

3. System Model

3.1 MIMO Signal Model

Multiple-Input Multiple-Output (MIMO) systems form a core component of modern wireless communication standards such as LTE, 5G NR, and future 6G networks. The fundamen- tal narrowband MIMO signal model is expressed as

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}, \tag{1}$$

where $\mathbf{y} \in \mathbb{C}^{N_r \times 1}$ is the received signal vector, $\mathbf{H} \in \mathbb{C}^{N_r \times N_t}$ is the channel matrix, $\mathbf{x} \in \mathbb{C}^{N_t \times 1}$ is the transmitted symbol vector, and $\mathbf{n} \in \mathbb{C}^{N_r \times 1}$ represents additive white Gaussian noise (AWGN) with zero mean and variance σ^2. Each transmitted symbol is drawn from a modulation constellation such as QAM.

3.2 Transceiver Operation

In a typical MIMO transceiver, input data bits are first encoded for error correction, then mapped to complex symbols and transmitted simultaneously across multiple antennas. At the receiver, the received signal is processed through channel estimation, equalization, and signal detection to recover the transmitted symbols. Finally, demodulation and decoding reconstruct the original bitstream. This architecture enables spatial multiplexing and diversity gains, improving spectral efficiency and link reliability [1–3].

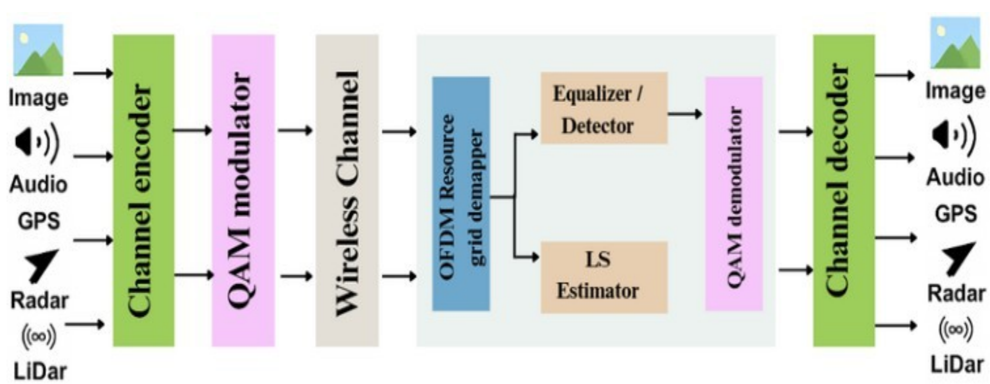

Figure 1: MIMO System Transmit-Receive Block Diagram

4. System Model

4.1 Channel Model Overview

In this work, we evaluate the performance of the Conjugate Gradient (CG) detector under various channel conditions in a basic MIMO system. Specifically, we consider both uncorrelated and spatially correlated channels to study how antenna correlation affects detection performance and convergence speed.

Uncorrelated channels serve as a baseline scenario, where each transmit-receive antenna pair experiences independent Rayleigh fading. In contrast, spatially correlated channels arise in practical deployments due to limited antenna spacing or environmental scattering, which introduces statistical dependencies between antenna elements. Understanding CG performance in both scenarios is critical for assessing its suitability in realistic 5G and 6G MIMO systems. For correlated channels, we adopt the Kronecker correlation model [10] with exponential correlation matrices for both transmitter and receiver sides. By varying the correlation coefficient and the number of CG iterations, we investigate the trade-off between computational complexity and detection accuracy, providing a comprehensive view of CG performance across different channel conditions.

4.2 Flat Fading Assumption

For simplicity, we assume flat-fading channels, where each transmit-receive antenna pair experiences a single complex gain that remains constant over the symbol period. This simplification allows us to focus on evaluating the CG detector without additional complications from frequency-selective fading, making it suitable for our basic MIMO simulations.

4.3 Correlated Channel Model (Kronecker)

In practical MIMO systems, the signals received at multiple antennas are often spatially correlated due to limited scattering or insufficient antenna spacing. To model this effect, we adopt the Kronecker correlation model [10]:

$$\mathbf{H}_{\text{corr}} = \mathbf{R}_{\text{rx}}^{1/2}\mathbf{H}_{\text{iid}}\mathbf{R}_{\text{tx}}^{1/2}, \tag{2}$$

where:

- $\mathbf{H}_{\text{iid}} \in \mathbb{C}^{N_r \times N_t}$ contains i.i.d. complex Gaussian entries $\mathcal{CN}(0, 1)$ representing an uncorrelated Rayleigh fading channel.
- $\mathbf{R}_{\text{rx}} \in \mathbb{C}^{N_r \times N_r}$ is the receive correlation matrix.
- $\mathbf{R}_{\text{tx}} \in \mathbb{C}^{N_t \times N_t}$ is the transmit correlation matrix.

We adopt the exponential correlation model, where each matrix entry is defined as:

$$[\mathbf{R}]_{i,j} = \rho^{|i-j|}, \quad 0 \leq \rho \leq 1, \tag{3}$$

with ρ being the spatial correlation coefficient.
In our simulations, we set $\rho_{\text{tx}} = 0.4$ for the transmit antennas and $\rho_{\text{rx}} = 0.7$ for the receive antennas. This setup corresponds to moderate correlation at the transmitter and higher correlation at the receiver. The Kronecker model is implemented in Sionna to fully define the correlated channel and ensure reproducibility of our results.

4.4 SNR Range Selection and Noise Power

The performance of the Conjugate Gradient (CG) detector is evaluated over a range of signal-to-noise ratio (SNR) values to study its robustness under different channel conditions. In our simulations, we consider SNR values from −10 dB to −1 dB, which represent challenging uplink scenarios commonly encountered in massive MIMO systems with many users or limited transmit power.
For a normalized transmitted signal vector with unit average power ($E[|x|^2] = 1$), the noise vector $\mathbf{n}$ is modeled as additive white Gaussian noise (AWGN) with variance:

$$\sigma^2 = \frac{N_t}{10^{\text{SNR}_{\text{dB}}/10}} \tag{4}$$

where N_t is the number of transmit antennas. This ensures that the SNR per receive antenna matches the desired simulation value. The following Table 4.4 shows the corresponding noise variance for selected SNR values.

Table 1 . Noise Variance Corresponding to SNR Values (for $N_t = 16$)

SNR (dB)	Linear SNR	Noise Variance σ^2
-10	0.1	10
-5	0.316	3.16
-1	0.794	1.26

Reason for chosen range At very low SNR (e.g., −10 dB), the noise dominates the received signal, making detection extremely challenging. This allows us to observe CG divergence behavior when the number of iterations is insufficient. At higher SNR (e.g., −1 dB), the signal power is comparable to noise, and the CG detector converges faster, showing near-LMMSE performance with fewer iterations. This SNR range also provides insight into numerical stability, since low SNR increases the relative magnitude of rounding errors in iterative methods.

5. Conjugate Gradient Detection

Conventional LMMSE detection involves inverting the matrix $(\mathbf{H}^H\mathbf{H} + \sigma^2\mathbf{I})$, which becomes computationally prohibitive in massive MIMO. Iterative methods such as the Conjugate Gradient (CG) algorithm approximate the LMMSE solution through successive iterations without explicitly computing the matrix inverse, achieving comparable detection performance at significantly reduced computational cost [4–6].

5.1 CG Algorithm

Table 1 summarizes the iterative steps of the CG detector used in this study.

Algorithm 1 CG Detector (based on [8])

Require: $\mathbf{A}$ and $\mathbf{b}$

Ensure: Estimated transmit signal vector $\hat{\mathbf{s}}$

Initialize $\hat{\mathbf{s}}^{(0)} = 0, \hat{\mathbf{r}}^{(0)} = \mathbf{b}, \hat{\mathbf{d}}^{(0)} = \hat{\mathbf{r}}^{(0)}$

while $\|\hat{\mathbf{r}}^{(i)}\| > \varepsilon$ **do**

  Compute step size: $\alpha^{(i)} = \frac{\langle \hat{\mathbf{r}}^{(i)}, \hat{\mathbf{r}}^{(i)} \rangle}{\langle \hat{\mathbf{d}}^{(i)}, \mathbf{A}\hat{\mathbf{d}}^{(i)} \rangle}$

  Update estimate: $\hat{\mathbf{s}}^{(i+1)} = \hat{\mathbf{s}}^{(i)} + \alpha^{(i)}\hat{\mathbf{d}}^{(i)}$

  Update residual: $\hat{\mathbf{r}}^{(i+1)} = \hat{\mathbf{r}}^{(i)} - \alpha^{(i)}\mathbf{A}\hat{\mathbf{d}}^{(i)}$

  Compute direction factor: $\beta^{(i)} = \frac{\langle \hat{\mathbf{r}}^{(i+1)}, \hat{\mathbf{r}}^{(i+1)} \rangle}{\langle \hat{\mathbf{r}}^{(i)}, \hat{\mathbf{r}}^{(i)} \rangle}$

  Update search direction: $\hat{\mathbf{d}}^{(i+1)} = \hat{\mathbf{r}}^{(i+1)} + \beta^{(i)}\hat{\mathbf{d}}^{(i)}$

  $i = i + 1$

end while

return $\hat{\mathbf{s}} = \hat{\mathbf{s}}^{(i)}$

Here, $\alpha^{(i)}$ controls the update magnitude, $\beta^{(i)}$ refines the conjugate search direction, $\hat{\mathbf{r}}^{(i)}$ is the residual vector, and $\hat{\mathbf{d}}^{(i)}$ is the search direction. Iterations continue until the residual norm $\|\hat{\mathbf{r}}^{(i)}\|$ is sufficiently small.

CG Divergence and Iteration Trade-Off. The CG algorithm is an iterative solver that approximates the LMMSE solution without directly inverting the channel matrix. For very few iterations, the residual vector may remain large, causing the detector to diverge or produce high BER, especially at low SNR where noise dominates. As the number of iterations increases, the residual decreases, and the BER approaches the LMMSE benchmark. This trade-off between number of iterations and detection accuracy is central to evaluating CG for massive MIMO systems.

5.2 Computational Complexity

After introducing the Conjugate Gradient (CG) algorithm, analyzing its computational complexity is crucial to assess efficiency against other detectors. This reveals the operations per iteration and overall cost relative to system dimensions, helping balance performance and load. Compared to direct methods like LMMSE, it guides the choice of iteration numbers for practical massive MIMO systems. Table 1 compares the computational complexity of LMMSE and CG detectors.

The LMMSE detector provides an exact solution but scales cubically with N_t, which is impractical for massive MIMO. The CG detector iteratively approximates the LMMSE solution

Table 1: Computational Complexity of LMMSE and CG Detectors

Detector	LMMSE	CG
Matrix inversion	$O(8N_t^3)$	–
Matrix-vector multiplication	$O(4N_t^2)$	$O(4N_t^2 + 4N_t + 4)$
Residual update	–	$O(4N_t^2 + 2N_t)$
Search direction update	–	$O(2N_t)$
Total complexity	$O(8N_t^3 + 4N_t^2)$	$O(L(8N_t^2 + 14N_t + 8))$

with per-iteration complexity $O(N_t^2)$. When the number of iterations $L \ll N_t$, CG achieves near-LMMSE performance with significantly lower computational cost, making it suitable for large-scale 5G and 6G systems.

6. Simulation Setup

6.1 Simulation Parameters

This setup, shown in Table 2, provides a scalable and reproducible test environment for analyzing detector behavior under realistic massive MIMO configurations. While the current evaluation focuses on the flat-fading MIMO case, the same CG-based detection process can be applied independently to each subcarrier in wideband MIMO systems, forming the foundation for future 6G experiments.

Table 2: Simulation Parameters and Configurations

Parameter	5G Configuration	6G Configuration
MIMO Setup	16 × 64	16 × 128
Modulation Scheme	16-QAM	128-QAM
Coding	5G LDPC (rate = 1/2)	5G LDPC (rate = 1/2)
Detector	CG vs LMMSE	CG vs LMMSE
Iterations	2, 5, 10, 16	2, 5, 10, 16
Metrics	BER, Residual Norm	BER, Residual Norm
Channel Type	Flat-Fading MIMO	Flat-Fading MIMO
Spatial Correlation	$\rho_{tx} = 0.4, \rho_{rx} = 0.7$	$\rho_{tx} = 0.4, \rho_{rx} = 0.7$
Tolerance	10^{-12}	10^{-12}

7. Results and Discussion

7.1 Effect of Spatial Correlation on 5G-BER

To evaluate the impact of spatial correlation on massive MIMO detection, we simulated a 16×64 5G MIMO system using the CG detector with multiple iteration counts. Two channel scenarios were considered: uncorrelated (i.i.d.) and correlated channels modeled using the Kronecker model with exponential correlation coefficients $\rho_{tx} = 0.4$ and $\rho_{rx} = 0.7$.

These Figures presents the BER performance over SNR values from −10 dB to −1 dB for both scenarios.

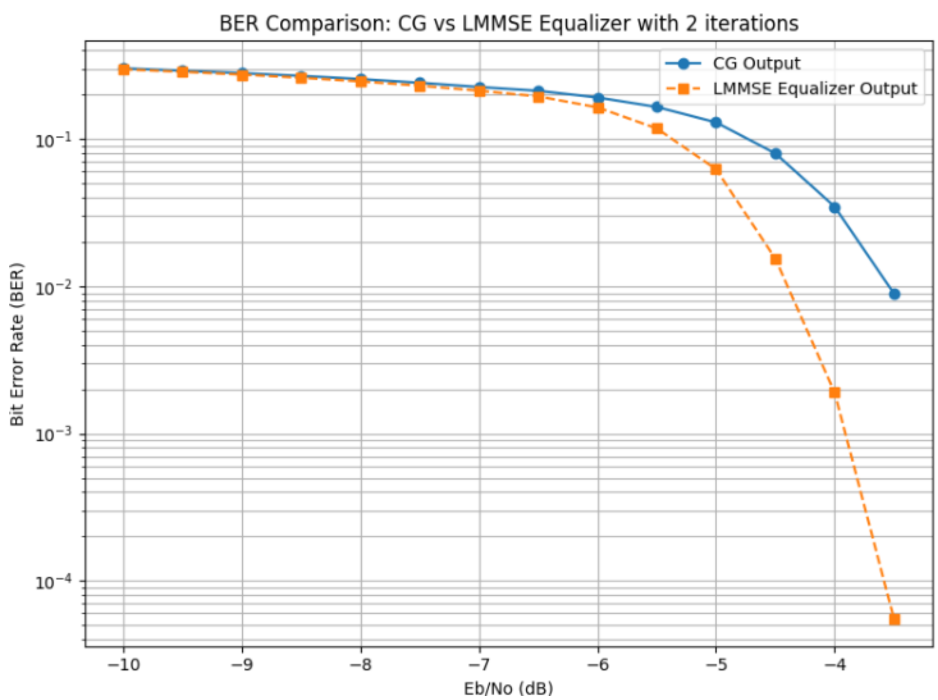

Figure 2: BER vs SNR for uncorrelated channel with 2 iterations.

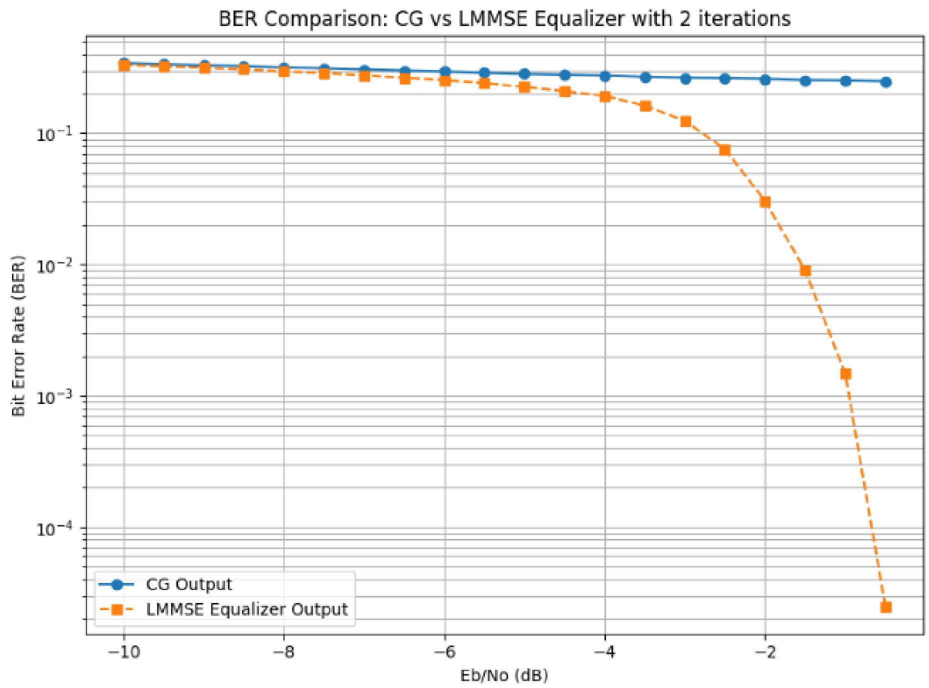

Figure 3: BER vs SNR for correlated channel with 2 iterations in 5G.

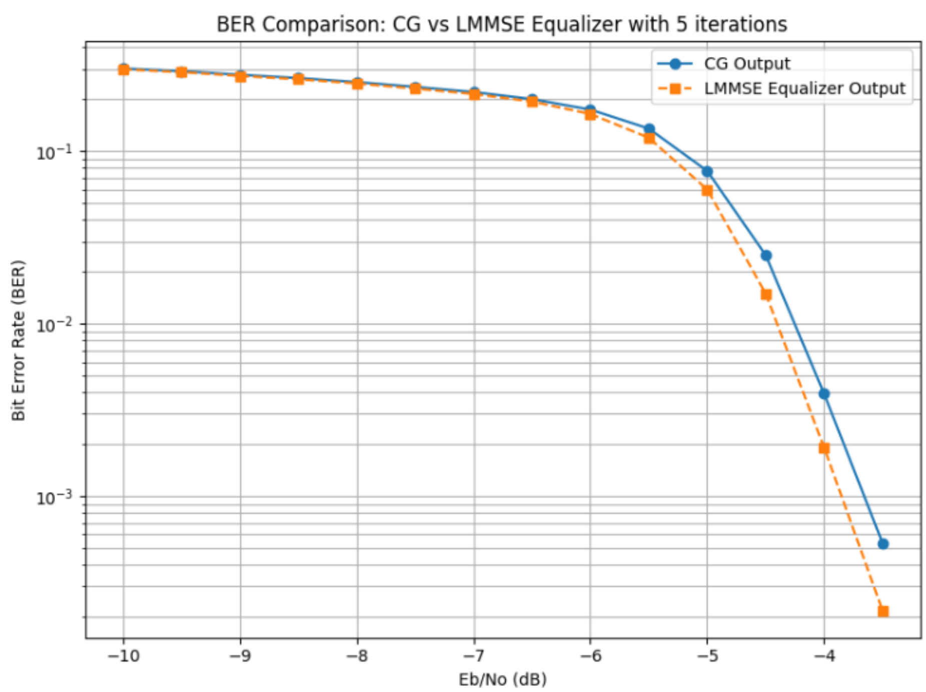

Figure 4: BER vs SNR for uncorrelated channel with 5 iterations in 5G.

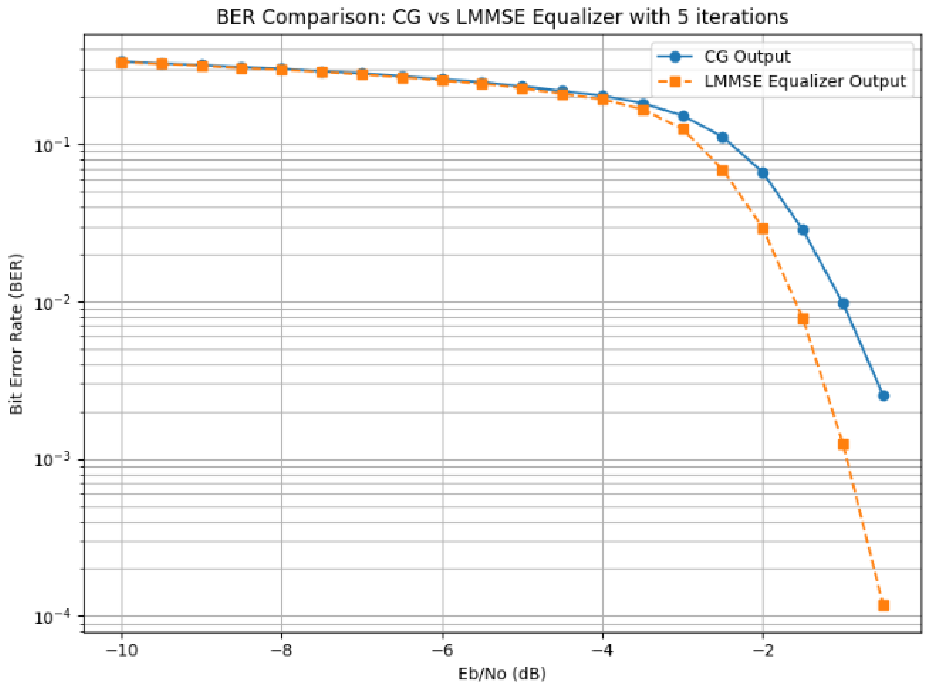

Figure 5: BER vs SNR for correlated channel with 5 iterations in 5G.

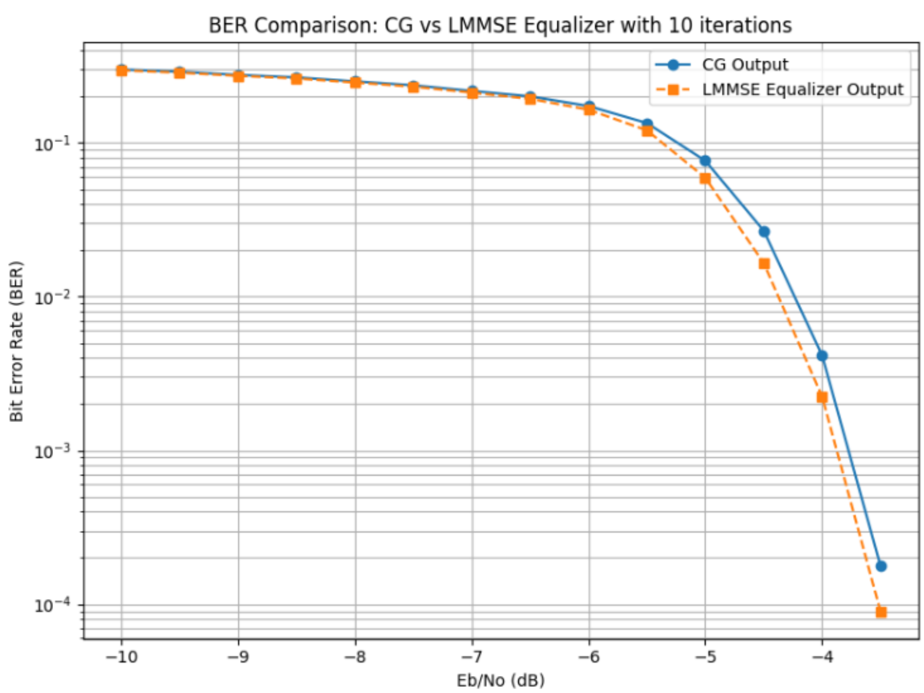

Figure 6: BER vs SNR for uncorrelated channel with 10 iterations in 5G.

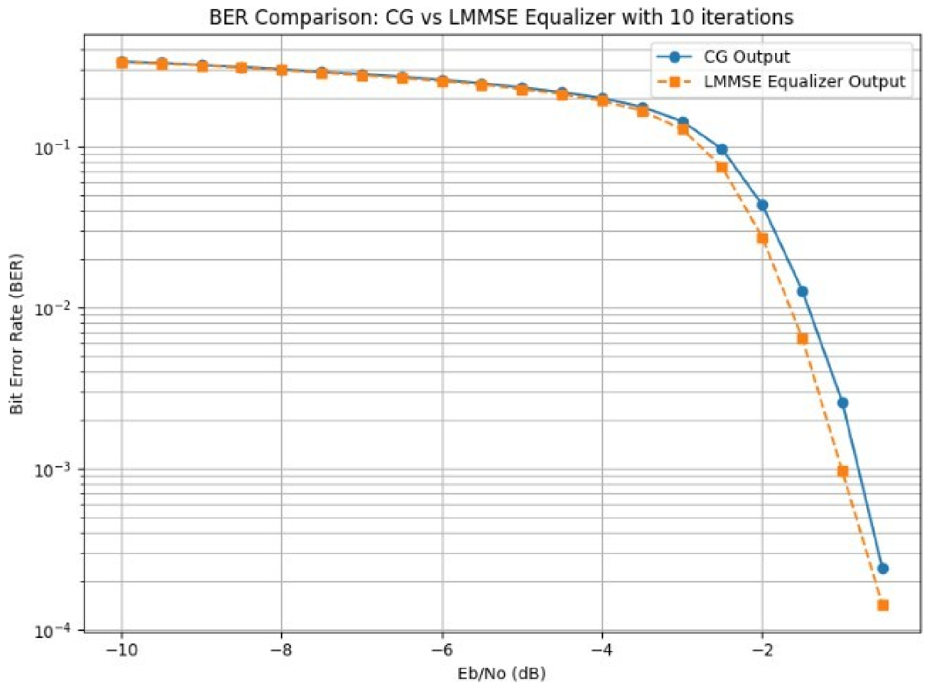

Figure 7: BER vs SNR for correlated channel with 10 iterations in 5G.

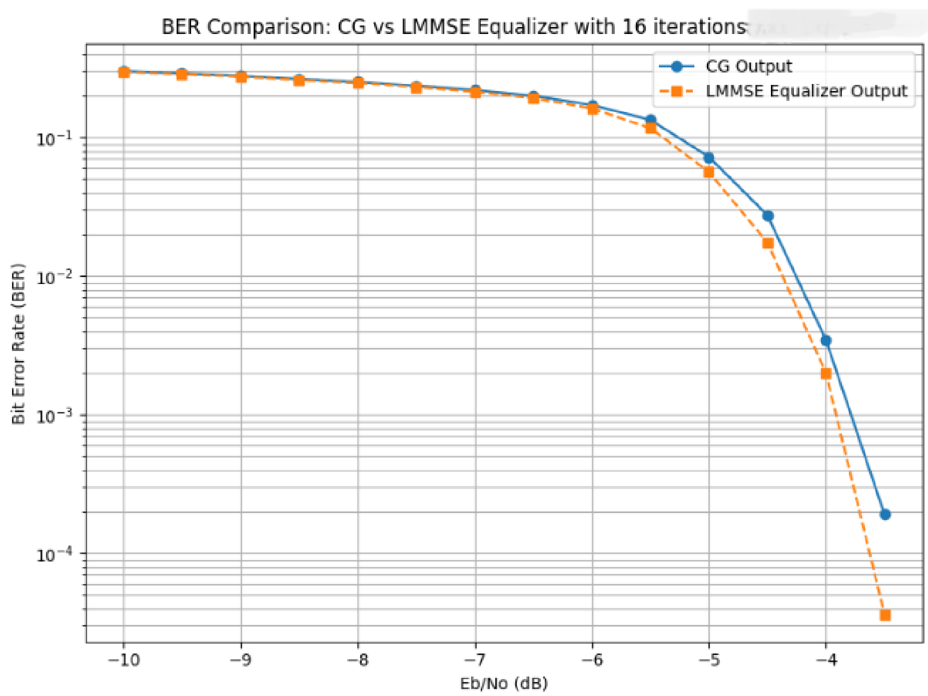

Figure 8: BER vs SNR for uncorrelated channel with 16 iterations in 5G.

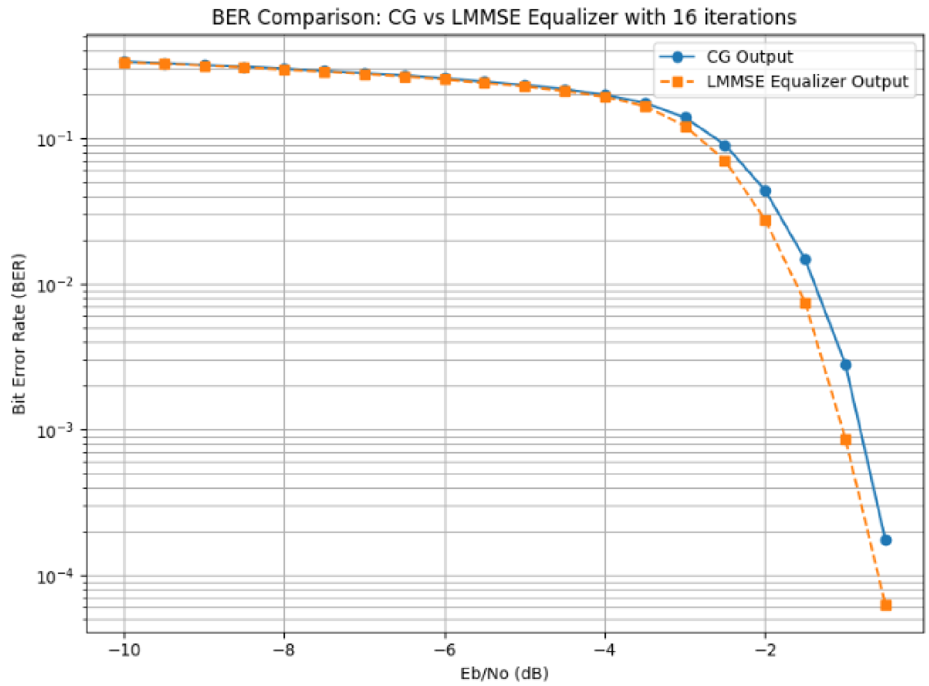

Figure 9: BER vs SNR for correlated channel with 16 iterations in 5G.

The results demonstrate that spatial correlation slightly increases BER compared to the uncorrelated case. This occurs because correlation reduces the effective rank of the channel matrix, which increases interference among transmitted streams and slows convergence of the CG detector. The effect is more pronounced at low SNR values where noise dominates the signal, highlighting that correlated channels are inherently more challenging for iterative detection.

These observations confirm that spatial correlation must be considered when evaluating the performance of CG-based detection algorithms in massive MIMO systems. Additionally, they illustrate the trade-off between channel conditions and detector performance: while CG approximates LMMSE effectively, its convergence and resulting BER are sensitive to the underlying channel correlation structure.

7.2 Performance of CG in Correlated 5G vs 6G Channels

Building upon the 5G results presented in the previous Section, we now evaluate the CG detector performance in correlated 5G and 6G MIMO channels. The goal is to investigate how the detector scales with increasing system size and higher-order modulation while maintaining near-LMMSE performance.

For this analysis, we focus on two representative iteration numbers, 5 and 10, to illustrate the trade-off between convergence speed and system dimensions.

As observed previously, spatial correlation affects BER in 5G; here we examine whether the same trend holds for larger 6G configurations and how additional iterations impact performance in both systems. These results demonstrate the scalability and robustness of the CG detector in massive MIMO systems under realistic correlated channels.

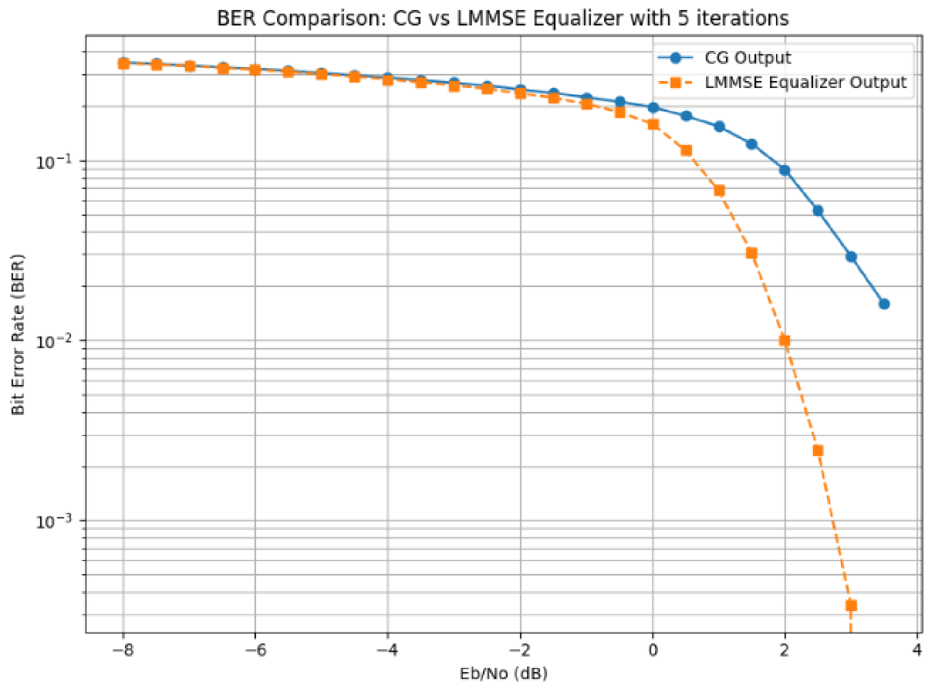

Figure 10: BER vs SNR for correlated channel with 5 iterations in 6G.

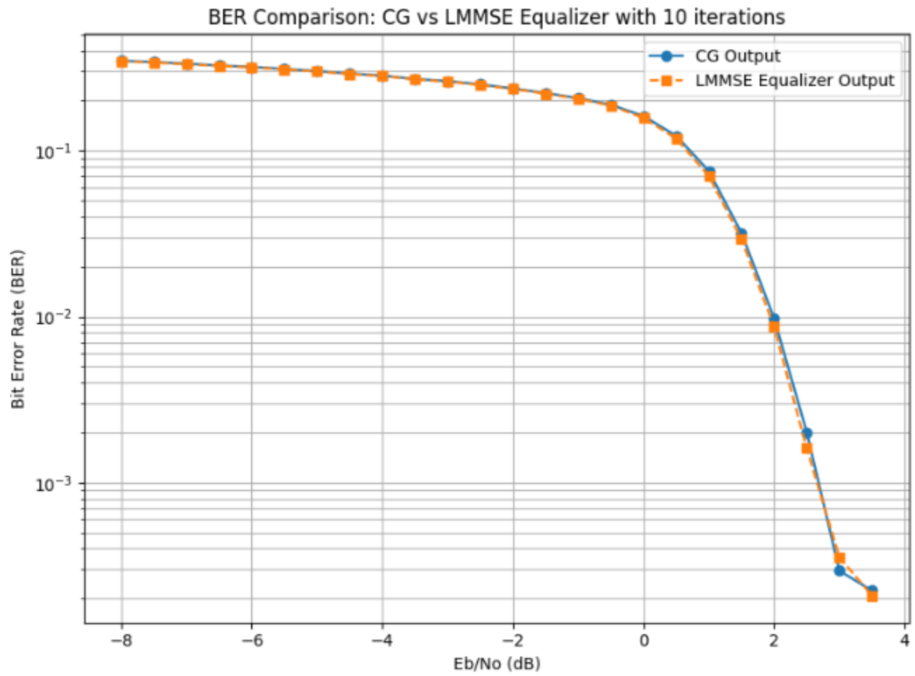

Figure 11: BER vs SNR for correlated channel with 10 iterations in 6G. We

can clearly observe that:

- For 5 iterations, the 5G system achieves slightly lower BER than 6G. This is due to the smaller channel dimension and lower-order modulation, which allow faster residual convergence in fewer iterations.
- For 10 iterations, the 6G system achieves better BER performance. With additional iterations, the larger 6G channel matrix benefits more from iterative refinement, allowing the CG detector to approach LMMSE-level performance and slightly surpass 5G in these settings.
- This demonstrates that CG's effectiveness depends not only on SNR and correlation but also on the number of iterations relative to system size and modulation order.

Overall, these results confirm that CG detection scales well with system dimensions and can achieve near-optimal performance in 6G massive MIMO with a reasonable number of iterations.

7.3 Residual Convergence Analysis

The residual norm $\|\mathbf{r}^{(i)}\|$ provides insight into the convergence of the CG detector. Fig. 12 shows the residual evolution for correlated 5G channels, while Fig. 13 shows the residuals for correlated 6G channels.

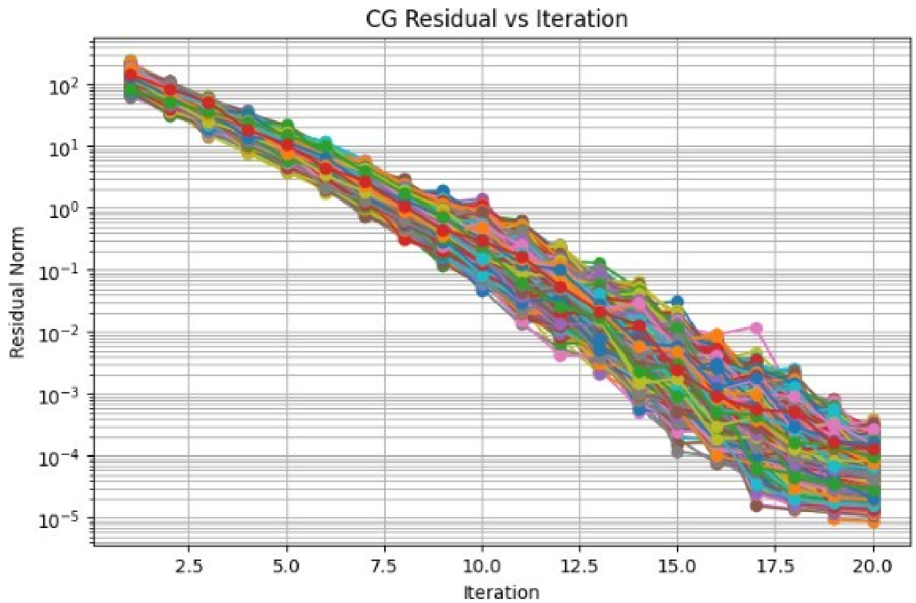

Figure 12: BER performance of the CG detector for 5G correlated and uncorrelated channels.

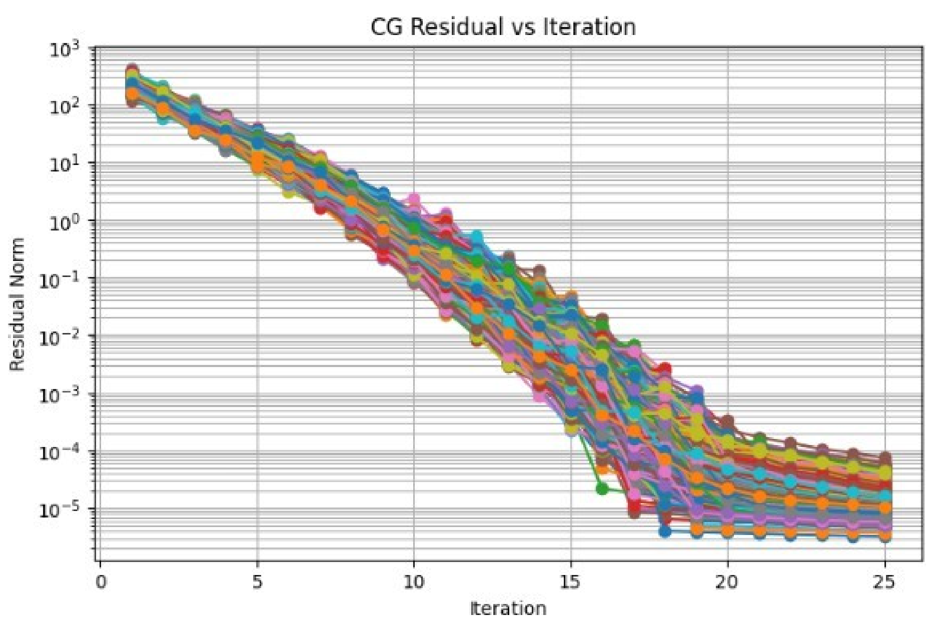

Figure 13: BER performance of the CG detector for 6G correlated and uncorrelated channels.

For 5G, the residual decreases rapidly with iteration count, and after 15 iterations, it is sufficiently small to ensure near-LMMSE detection accuracy. For 6G, the initial residual is higher due to the larger system size and higher modulation order, but it also converges with sufficient iterations. These residual trends explain the BER behavior observed:

At low iteration counts, residuals remain large, resulting in higher BER, especially for correlated channels.

As iterations increase, residuals reduce and BER approaches the LMMSE benchmark.

The comparison between 5G and 6G shows that CG scales well, achieving similar convergence and performance with a reasonable number of iterations.

The results show that CG converges more slowly in larger MIMO systems due to the increased number of unknowns, while channel correlation slightly slows convergence by increasing the condition number. A convergence threshold of 10^{-12} ensures near-LMMSE accuracy without unnecessary computation. Overall, the residual analysis confirms that CG closely approximates the LMMSE solution and indicates how many iterations are needed for different system sizes and channel conditions.

7.4 Computational Complexity

The computational complexity of the Conjugate Gradient (CG) detector, measured in memory cost (bits), depends strongly on the number of iterations. With 10 iterations, CG requires 22,820 bits, which is lower than the 33,792 bits needed by the LMMSE detector. However, increasing the number of iterations to 20 raises CG's memory usage to 45,640 bits, surpassing LMMSE. This behavior is consistent in both 5G and dense 6G configurations with $N_t = 16$ transmit antennas. It highlights an important trade-off: CG is more efficient when the number of iterations is smaller than the number of transmit antennas, but becomes more resource-intensive if this threshold is exceeded, which is a key consideration in massive MIMO system design.

8. Conclusion

In this paper, we investigated the Conjugate Gradient (CG) detector as a low-complexity alternative to LMMSE for massive MIMO systems in 5G and 6G scenarios. We analyzed its performance over both uncorrelated and correlated flat-fading channels and evaluated the impact of iteration numbers on BER and residual convergence. Simulation results demonstrated that CG achieves near-LMMSE detection accuracy while significantly reducing computational complexity for a moderate number of iterations. Furthermore, spatial correlation slight degrades performance, but CG remains robust, and its efficiency scales well with system dimensions.

These findings confirm that CG-based detection is a practical and scalable solution for real-time massive MIMO deployments, providing an effective trade-off between performance and complexity in next-generation wireless networks.

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