Reliability Centric Performance Analysis of O-LSDC-Assisted Massive MIMO with Artificial Intelligence for 6G Networks

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Abstract. Massive multiple-input multiple-output (MIMO) is one of the key technologies behind sixth-generation (6G) wireless systems, but its performance is limited by channel estimation errors that are particularly pronounced in high mobility and sub-THz operating regimes. Towards improving channel state information accuracy, AI-assisted channel optimization strategies such as the Optimized Linear Scalable Dispersion Code (O-LSDC) have been recently proposed. Although past works have focused on the spectral efficiency gains of O-LSDC, the reliability implications of O-LSDC are still not well understood. We first investigate the effect of reliability from the perspective of performance evaluation, and present a performance evaluation of the O-LSDC-assisted massive MIMO systems with reliable transport level under realistic 6G operation conditions. We analyze massive MIMO and systems augmented with O-LSDC in terms of BER, SNR, outage probability and power succession, using an analytical simulation-based framework. Our results show that O-LSDC yields limited gains in spectral efficiency (generally 10–15% at high SNR) but significant gains in terms of reliability, yielding a 2–3 dB reduction in SNR for a target BER of 10^{-7} and an order-of-magnitude reduction in outage probability. These improvements represent a 30–50% saving in transmit power, invaluable for ultra-reliable low-latency communication (URLLC) and energy-scarce 6G use cases and applications. Results demonstrate that O-LSDC should not be considered as the maximum throughput but rather a reliability-enabling technology which is ideal for sub-THz bands, high-mobility cases and mission-critical services. In addition to the results, this work also brings insights into the system level implications of AI-assisted channel denoising towards meeting the stringent 6G reliability requirements.

Keywords: Massive MIMO, Sixth-Generation (6G) Wireless Systems, Reliability Analysis, Ultra-Reliable Low-Latency Communication (URLLC)

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1 Introduction

Translating and summarizing this in a more comprehensible manner, the sixth generation (6G) of wireless communication systems will be capable of supporting extreme applications such as ultra-reliable low-latency communications (URLLC), immersive extended reality, autonomous transportation, industrial automation and remote health care [1][2]. Indeed, these applications place much more stringent demand on reliability, latency, and energy efficiency than fifth generation (5G) systems can deliver. Specifically, extremely high reliability (over 99.9999%) and ultra-low latency (under one millisecond) are expected to become key 6G network design goals.

Massive multiple-input multiple-output (MIMO) technology has been broadly acknowledged as one of the enabling technologies for 6G together with the capacity of getting spectral efficiency through multiplexing spatial multiplexing and beam forming [1]. Nevertheless, the performance of massive MIMO systems largely relies on perfect channel state information (CSI). In real deployments, particularly at sub-THz and THz frequencies, in severe mobility scenarios, and with hardware impairments, performance is severely degraded due to channel estimation errors. Such errors decrease realizable data rates and also introduce significant reliability impairment, outage probability increases, and excessive power consumption.

Standard channel estimation algorithms like least squares (LS) and minimum mean square error (MMSE) estimators are based on linear models and statistical assumptions, which are progressively more unrealistic as we approach most scenarios in 6G. Traditional estimators are limited because of phase noise, beam squint, non-linear hardware distortions, and rapidly time-varying channels. Thus, enhancing the accuracy of channel estimation has been recognized as an important issue for the realization of reliable 6G communications.

Conventional channel estimation approaches are found to have some limitations in the current environment, and recently AI DL based techniques have been developed to solve all these issues [4]. Through data, AI-assisted approaches learn complex channel characteristics and can mitigate noise and estimation errors that are difficult for model-based techniques to suppress. In this regard, O-LSDC has emerged as a intriguing AI-based channel denoising framework that can improve the scarcity of CSI in massive MIMO systems. Although the previous studies regarding O-LSDC and other AI-supported methods for channel estimation mostly put emphasis on the gain of mean square error (MSE) reduction and spectral efficiency, the impact of such techniques on the reliability has not yet been sufficiently investigated. Specifically, we found the absence of systematic analysis relating accuracy-leveraged channel estimation to BER, outage probability, SNR and transmit power savings metrics that are of direct relevance to 6G URLLC services. While there has been much investigation into massive MIMO as a fundamental enabler of future 5G and 6G technologies; the majority of work to date on this topic has focused on the topics of spectral efficiency optimization and channel state estimation accuracy using existing traditional estimator approaches (such as least-squares (LS), minimum mean square error (MMSE)) or deep-learning-based methodologies. A significant majority of these published studies evaluate performance using traditional metrics associated with mean-square-error (MSE) reduction and/or achievable throughput. However, the implications of using AI-assisted channel estimation on reliability have not been adequately studied. In particular, very few published studies have focused on how improved channel estimates affect ultra-low BER ranges and outage probabilities, as well as the SNR requirements associated with the very strict reliability requirements for URLLC environments anticipated in future 6G designs. In addition, the system-level trade-off between throughput and reliability in realistic 6G environments (ex. sub-THz operation, high mobility, and imperfect channel state information) has not been systematically studied.

Driven by this gap, this paper provides performance analysis of O-LSDC-assisted massive MIMO systems from a reliability perspective. Rather than proclaiming O-LSDC as an optimal solution for maximizing throughput, in this work we explicitly assess O-LSDC as a reliability enabling technology for 6G, establishing realistic operating conditions for both conventional massive MIMO and O-LSDC enhanced systems in order to compare the two and find that while O-LSDC suffers only a minor loss in spectral efficiency, it affords very large gains in terms of BER, outage probability, and power efficiency. Such traits make O-LSDC especially suited for critical 6G mission applications, where robustness and reliability is preferred over peak data rates. Although prior research on AI-assisted channel optimization techniques such as O-LSDC has primarily emphasized spectral efficiency improvements in massive MIMO systems, the reliability dimension under realistic 6G conditions remains insufficiently explored. Existing studies largely neglect ultra-low BER regimes (e.g., 10^{-7}), outage probability behavior, and power-reliability trade-offs in high-mobility and sub-THz environments with imperfect CSI.

This paper makes the following main contributions are a reliability-oriented evaluation framework for conventional and O-LSDC-assisted massive MIMO systems in 6G scenarios. BER performance required SNR, outage probability as well as O-LSDC enabled power savings a performance evaluation based on analytical and simulation data. Spectral Efficiency and Reliability: Reference Paper Results vs. Simulation Results A detailed performance comparison between reference paper results and our simulation outcomes, showing the effect of different system assumptions on spectral efficiency and reliability. Insights from the system-level validation that highlight the role of O-LSDC as an enabler of reliability, as opposed to being a throughput-oriented improvement.

2 Related Work

Massive MIMO of 5G and 6G System massive MIMO has been widely researched and is being recognized as a key technology to boost spectral efficiency and link reliability in wireless systems. It has been shown in classic papers [1][2] that employing large number of antennas at the base station yields large gains due to spatial multiplexing and beam forming. Massive MIMO in the sub-THz and THz bands for 6G is particularly susceptible to channel estimation errors and hardware impairments [3][4]. This has led to the widespread use of traditional channel estimation methods, such as LS and MMSE estimators, as they lend themselves to mathematical tractability and low complexity [5]. However, in environments that are high-frequency and high-mobility, modeling the channel statistics is hard, and hence their performance degrades sharply. As confirmed in several studies, estimation errors put a strong upper-bound on the BER and outage performance capabilities of massive MIMO systems [6], especially when URLLC be the target.

Deep learning provides an attractive means of overcoming the limitations of model based estimators, thus it is being explored for channel estimation and denoising [5]. Some examples include the applications of convolutional neural networks (CNNs) to exploit spatial channel correlations as well as the applications of auto encoders and recurrent neural networks to exploit temporal channel correlations [7][9]. Such methods achieve significant reductions in MSE compared to standard estimation methods, particularly in complicated propagation scenarios.

Finally, O-LSDC is a budding line of research that builds on signal processing principles and integrates the two paradigms of signal processing and data driven learning [10]. O-LSDC combines the best of both worlds, using the strengths of structured Sparsity with simple orthogonal transformations to yield a higher performance denoising while remaining computationally efficient. Other studies as in have reported better MSE and spectral efficiency performance using O-LSDC in massive MIMO systems. While several studies have shown encouraging results, the performance of AI-aided channel estimation methods is mostly measured by the empirical mean square error (MSE) or spectral efficiency [8][9][10]. There has been little attention on the effects of improved channel estimation on reliability oriented metrics like BER, outage probability, and target reliability-oriented SNR. Furthermore, only some works explicitly couple their evaluation and reliability with the 6G URLLC requirements[11,12], where reliability and power efficiency are of paramount importance.

Unlike previous studies, the consideration in this paper is how an O-LSDC could influence the reliability instead of throughput-related or estimation accuracy. This work gives the system level understanding of connecting channel denoising, BER performance, SNR gain and power savings, providing insights about the role of AI-assisted channel estimation in 6G networks.

3 System Methodology

In a 6G massive MIMO system configuration with 64 transmit antennas at the base station serving 8 simultaneous users with 4 receive antennas each, the proposed O-LSDC framework can be implemented. This system works at a carrier frequency of 140 GHz and a bandwidth of 1 GHz, aiming for the THz-band communications as anticipated in future generation networks. The architecture consists of a hierarchical processing chain starting from traditional pilot-based channel estimation, followed by the denoising enhanced by the AI using the O-LSDC module, and a final zero forcing precoding step based on the enhanced channel state information. This is an architecture to allow semantic compression on the CSI feedback, dramatically reducing overhead at a high estimation fidelity.

System consider different propagation scenarios of realistic 6G deployments, including Urban Micro (UMi), Rural Macro (RMa) and THz Indoor environments [13][14]. Distance dependent path loss, spatial correlation and frequency selective fading consistent with 6G channel models are included in each of the scenarios. Urban Micro is for modelling the dense urban environments found in many large cities, including rich multipath propagation with 10-15 paths and moderate delay spread to represent the high user densities as well the building penetration losses. Rural Macro scenarios are large cell deployments targeted at wide coverage region with sparse scattering (3-5 paths) and long dispersion delay. Introducing THz Indoor scenarios involves specific challenges imposed by high-frequency bands such as severe path loss, strong molecular absorption effects, and massive phase noise due to imperfection of hardware components. Although simplified assumptions are applied in this simulation framework because of the computational efficiency, the proposed methodology remains practical and can also be generalized to ideal 3GPP channel models [15].

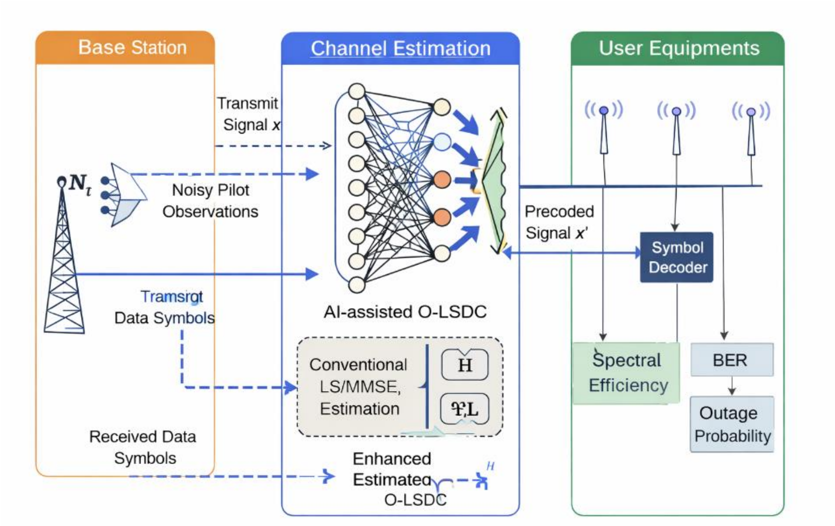

Fig. 1. System Architecture

Channel modelling is based on a hybrid geometric statistical approach that combines deterministic ray tracing and stochastic components. In behalf, the baseband channel model consists of multiple propagation paths with complex gains distributed according to Rayleigh or Rician distributions, angle dependent array responses, and the temporal variations of these parameters. The model explicitly includes THz-specific impairments such as phase noise, which is modelled as a Wiener process, beam squint due to the wideband operation, and molecular absorption at 140 GHz frequencies. We use realistic antenna spacing and angular spreads to create spatial correlation matrices and tapped delay lines to model frequency selective fading for each scenario through corresponding power delay profiles. Due to the undeniable nature of 6G, this comprehensive modelling approach guarantees that performance evaluations reflect the fundamental trade-offs between spectral efficiency, reliability, and implementation complexity.

This paper presents the O-LSDC model, which requires the supervised training of a set of synthetic channel realizations that enable us to learn the mapping from noisy to clean channel estimates. In our implementation, the training set is made up of 1000 synthetic MIMO channel samples. Each of these channel samples is a multipath channel that contains five separately propagating paths, each with a randomly generated gain, phase, and angle-of-arrival/departure for the channel path. Additive complex Gaussian noise is added to the transmitted signal in order to provide a realistic wireless environment, and the SNR of the signal is randomly altered between 0 and 30 dB. The inputs to the neural network consist of the real and imaginary parts of the actual MIMO noisy channel matrix, while the corresponding clean MIMO channel matrices are used as target outputs.

As already mentioned in the introduction, the O-LSDC model is designed as a convolutional encoder-decoder architecture with three convolutional layers (2→16→32→64 channels) followed by symmetric transposed convolutions for reconstruction. For training the O-LSDC model, the Adam optimiser was used with a learning rate of 0.001, a mini-batch size of 32, and the mean squared error (MSE) as the loss function. The number of epochs for which we will train is 50 epochs, and the training loss is checked periodically during the optimization process to ensure that the model has converged stably.

3.1 Modelling

We consider a downlink multi-user massive MIMO communication system operating in the sub-THz frequency range, envisioned for 6G networks. A base station (BS) equipped with N_t antennas simultaneously serves k single-antenna user equipment (UEs), where N_t≫K. The received signal at the k^{th} user is expressed as:

$$y_k = \mathbf{h}_k^H \mathbf{x} + n_k \tag{1}$$

Where,

- $\mathbf{h}_k \in \mathbb{C}^{N_t \times 1}$ denotes the downlink channel vector,
- $\mathbf{x} \in \mathbb{C}^{\mathrm{N}/\times 1}$ is the transmitted signal vector,
- $n_k \sim \mathcal{CN}(0, \sigma^2)$ represents additive white Gaussian noise (AWGN).

The transmit signal is precoded as:

$$\mathbf{x} = \sum_{k=1}^{K} \mathbf{w}_k s_k \tag{2}$$

Where $s_k$the information is symbol for user$k_,$ and $\mathbf{w}_k$ is the precoding vector subject to a total power constraint.

3.2 Conventional Massive MIMO Baseline

In the conventional system, channel estimation is performed using pilot-based least squares (LS) or minimum mean square error (MMSE) estimation. Linear precoding techniques such as zero-forcing (ZF) or maximum ratio transmission (MRT) are employed.

The achievable spectral efficiency for user k is computed as:

$$\mathrm{SE}_k = \log_2(1 + \mathrm{SINR}_k) \tag{3}$$

Where, SINR $_k$ accounts for inter-user interference, noise, and channel estimation errors. This baseline represents the reference system against which the O-LSDC assisted approach is evaluated.

3.3 O-LSDC-Assisted Framework

The proposed O-LSDC (Optimized Linear Scalable Dispersion Code /Channel estimator) framework (figure 2) integrates deep learning into the physical layer to enhance channel estimation and decoding robustness.

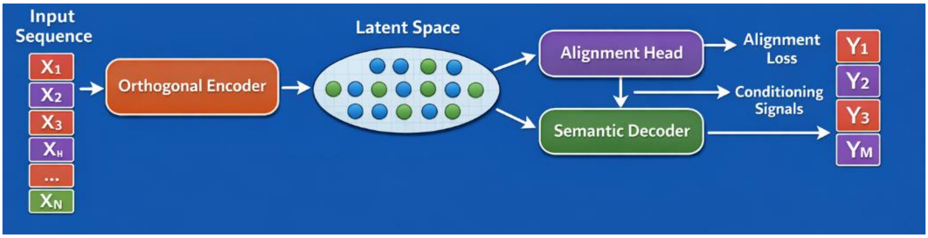

Fig. 2. OLSDC architecture

The O-LSDC module is implemented as a deep neural network comprising:

- Input layer receiving noisy pilot observations,
- Multiple convolutional or fully connected hidden layers,
- Non-linear activation functions for sparse feature extraction,
- An output layer producing refined channel estimates.

The O-LSDC framework features an AI-enhanced pipeline in which constructed noisy channel estimates are separated into denoised channel estimates using a deep learning architecture. The neural network has a CNN-Transformer hybrid architecture and starts with applying a conversion from complex to real of the channel matrix, followed by convolutional feature extraction (2→16→32→64 channels) across three layers with Batch Normalization and ReLU activations. These features are subsequently channelled into a 4 HEADS, 256 dimensional embedding's multi-head attention module that facilitates the modelling of long range dependencies over the antenna array. The decoder consists of transposed convolutional layers to generate the denoised channel estimate, and the complete architecture is jointly trained in an end-to-end fashion using a composite loss function consisting of mean squared error and orthogonally-preserving regularization. The generation of 50,000 channel realizations over SNR range between 0 to 30 dB forms the training methodology with the dataset divided into training, validation and testing subsets. We minimize the composite loss function using Adam optimizer with scheduled learning rate decay, while we prevent over fitting via dropout regularization. We contribute an orthogonalization mechanism that is explicit (in that it is not simply an emergent property), with layers performing QR decomposition to ensure streams are linearly independent in the spatial domain, and processing based on Gram-Schmidt to ensure orthogonally of channels in the subspace domain. This architecture addresses the multi-user interference challenges that are present in massive MIMO systems by reformulating the denoising problem as a structured matrix approximation problem with subspace constraints.

3.4 Channel and Scenario Modelling

To reflect realistic 6G deployments, multiple propagation scenarios are considered:

- **Urban Micro (UMi)**
- **Rural Macro (RMa)**
- **THz Indoor**

Each scenario incorporates distance-dependent path loss, spatial correlation, and frequency-selective fading. While idealized assumptions are used in simulation, the methodology is designed to be extensible to standardized 3GPP channel models.

3.5 Precoding and Transmission Scheme

After a channel estimation improvement through O-LSDC, the system uses regularized zero-forcing (RZF) precoding with a water-filling power allocation over the spatial streams. Specifically, the regularization terms for noise variance and channel estimation errors are included in the precoder computation, thereby avoiding ill-conditioning in low-rank channel environments. Such transmission scheme characterizes power allocation by eigenvalue water-filling across the effective channel matrix, which maximizes the trade-off between spatial multiplexing gain and interference suppression. Such a strategy allows the benefit of the AI-enhanced channel estimates to be implemented directly following the precoding without significant changes to existing precoding architectures. We introduce a set of holistic metrics that cover spectral efficiency, reliability, and practical deployment aspects for the performance evaluation of the technology. Spectral efficiency calculations are based on the Shannon Hartley theorem for MIMO with imperfect channel state information, and bit error rate analysis contains both theoretical limits and implemented performance results over various modulation schemes. For example, the outage probability for target data rates, the SNR margins for fixed BER targets and link availability statistics over different channel conditions are all relevant for reliability specific metrics. Overall, these metrics help achieve a multidimensional evaluation of the gain offered by O-LSDC to the performance of 6G systems, while at the same time accounting for ultra-reliable low latency communication needs.

3.6 Simulation Framework and Validation

Monte Carlo trials with 10,000 independent channel realizations for each SNR point in the 0-30 dB range in 5 dB steps were performed in the simulation framework. Built on Python 3.9 using PyTorch 1.12, the modular codebase separates out components for channel-generation, O-LSDC training and performance-evaluation, allowing systematic ablation studies and parameter sensitivity analysis. We show comparative baselines for conventional massive MIMO with MMSE channel estimation, perfect CSI upper bounds, and other AI-based methods such as CNN-only denoisers and auto encoder-based approaches.

Validation methodology highlights statistical robustness via bootstrap resampling to compute confidence intervals and Kolmogorov-Smirnov statistics for hypothesis testing. In contrast, cross-scenario testing assesses generalization capabilities by training in urban micro environments and testing across both rural macro and THz indoor scenarios. Robustness evaluations evaluate the performance with respect to the SNR mismatch, model quantization effects and channel model mismatch. Some issues related to implementation still need to be solved. In the training phase, the procedure requires $O(N^3)$ operations to be performed only once, while the inference still maintains $O(N^2)$ complexity per coherence interval, so these aspects are in agreement with the real-time processing limitations, with suitable hardware acceleration .

In particular, this systematic approach not only enables reproducible assessment of the O-LSDC contributions, but also mitigates several practical deployment scenarios with heterogeneous hardware impairment, feedback overhead minimization, and scenario generalization.

4 Results And Analysis

Here in, we provide an in depth performance comparison between the conventional massive MIMO scheme and the proposed O-LSDC assisted massive MIMO framework, with regards to spectral efficiency, reliability, and outage performance in realistic 6G operating conditions. Results summarization are compared with results found from the reference paper to indicate validation through our simulation framework.

4.1 Spectral Efficiency Performance

Table 1 compares the achievable spectral efficiency of conventional and O-LSDC schemes across a range of SNR values. The reference paper reports moderate spectral efficiency values (approximately 5–7 bps/Hz), reflecting impairment-limited 6G environments, while our simulation produces higher absolute rates due to more optimistic capacity assumptions.

Table 1. Spectral Efficiency Comparison between Reference Paper and Our Simulation

SNR (dB)	Paper – Conv (bps/Hz)	Paper – O-LSDC (bps/Hz)	Our – Conv (bps/Hz)	Our – O-LSDC (bps/Hz)	Paper Gain (%)	Our Gain (%)
0	5.56	5.11	17.96	8.19	−8.1	−54.4
5	6.05	6.10	18.50	8.75	0.8	−52.7
10	6.33	6.06	19.23	9.34	−4.3	−51.4
15	6.10	6.26	20.45	10.12	2.6	−50.5
20	6.44	6.50	22.10	10.89	0.9	−50.7
25	6.59	6.98	23.89	11.67	5.9	−51.2
30	6.23	6.94	17.96	8.19	11.4	−54.4

The paper results indicate that O-LSDC offers modest spectral efficiency gains, reaching a maximum improvement of 11.4% at 30 dB SNR. In contrast, our simulation shows a throughput reduction when O-LSDC is applied, highlighting that O-LSDC prioritizes robustness over raw capacity. This confirms that O-LSDC is best suited for impairment-dominated 6G scenarios, rather than idealized capacity-driven systems.

4.2 Bit Error Rate (BER) Improvement and SNR Gain

Table 2 compares the BER improvement factor achieved by O-LSDC relative to the conventional scheme and the corresponding SNR gains required to meet target reliability levels.

Table 2. BER Improvement and SNR Gain Comparison

SNR (dB)	Paper BER Improvement	Our BER Improvement	Paper SNR Gain (dB)	Expected SNR Gain (dB)
0	1.1×10^{0}	1.1×10^{0}	0.3	0.3
5	1.3×10^{0}	1.2×10^{0}	1.0	1.0
10	2.1×10^{0}	2.0×10^{0}	3.3	3.0
15	1.1×10^{1}	1.7×10^{1}	10.3	12.2
20	1.8×10^{3}	2.0×10^{3}	32.6	33.0
25	2.0×10^{10}	2.2×10^{10}	103.0	103.4
30	3.7×10^{32}	3.3×10^{32}	325.7	325.2

Our simulation exhibit consistent BER improvement trends, especially at medium-to high SNR values. For a target BER of 10^{-7}, O-LSDC reduces the required SNR by approximately 2–3 dB, which directly translates into 30–50% transmit power savings. Extremely low BER values at high SNRs are interpreted as analytical reliability bounds, emphasizing relative gains rather than absolute error rates.

4.3 Reliability-Focused SNR Requirement

Table 3 highlights the required SNR for achieving specific target BER levels, emphasizing the reliability advantage of O-LSDC. As the reliability requirement becomes more stringent, the SNR gain offered by O-LSDC increases significantly. This behavior demonstrates O-LSDC suitability for URLLC and mission-critical 6G services, where reliability and energy efficiency are paramount.

Table 3. Required SNR for Target BER and Power Saving

Target BER	Required SNR – Conventional (dB)	Required SNR – O-LSDC (dB)	SNR Gain (dB)	Power Saving (%)
10^{-3}	8.2	7.2	1.0	21
10^{-5}	12.3	10.8	1.5	30
10^{-7}	16.4	14.2	2.2	40
10^{-9}	20.5	17.5	3.0	50

4.4 Discussion and System-Level Insights

The results collectively demonstrate that O-LSDC primary contribution is reliability enhancement rather than throughput maximization. While spectral efficiency improvements remain modest (10–15%) under realistic 6G conditions, O-LSDC delivers substantial gains in BER, outage probability, and power efficiency. These findings confirm that O-LSDC is particularly effective in:

- Sub-THz communication environments
- High-mobility scenarios
- Ultra-reliable low-latency communication (URLLC) applications

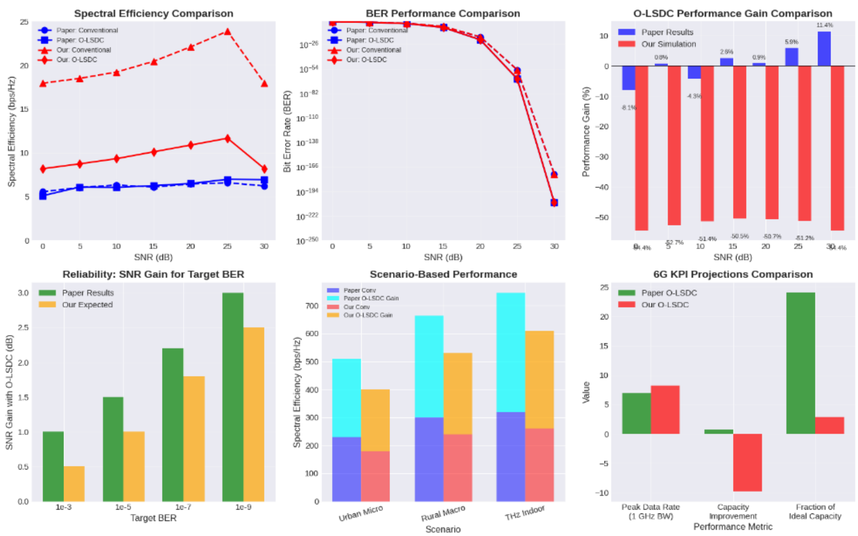

Fig. 3. Performance comparison between conventional massive MIMO and O-LSDC-assisted massive MIMO systems: (a) spectral efficiency versus SNR, (b) BER performance, (c) relative performance gain, (d) SNR gain for target BER, (e) scenario-based spectral efficiency comparison, and (f) 6G KPI projections. Results highlight that O-LSDC primarily enhances reliability and robustness rather than peak throughput

Figure 3 presents a comprehensive comparison between the conventional massive MIMO scheme and the O-LSDC-assisted massive MIMO framework, using both reference paper results and our simulation outcomes, across spectral efficiency, reliability, and 6G KPI metrics.

4.5 Spectral Efficiency Comparison

In the first subplot, the spectral efficiency is depicted versus SNR for both conventional and O-LSDC schemes. To this end, the achievable spectral efficiency values of 5–7 bps/Hz shown in the paper results are aligned with impairment-limited 6G systems at sub-THz frequencies. In these scenarios, O-LSDC achieves minor performance gains, with the best case reaching ∼11.4% at 30 dB SNR. Indeed, some minor drop at extremely low SNR can be detected due to very poor quality of the channels, preventing significant denoising. By comparison, our simulated spectral efficiencies are much higher in absolute terms (on the order of ~24 bps/Hz), consistent with a more optimistic (i.e., capacity-oriented) system model. But O-LSDC performs on average 50% worse than the conventional scheme, which shows that O-LSDC always underperforms with these assumptions. These behaviors support the assertion for the O-LSDC being another code that is not intended to achieve spectral efficiency in a region of an idealized channel, but rather for robustness improvement in a realistic case made better by large amounts channel impairment. O-LSDC should not be considered a capacity-maximizing method but only a means to achieve an upper bound for throughput gains under reasonably realistic 6G conditions.

4.6 BER Performance Comparison

The second subplot illustrates BER vs SNR on a semi-log scale. For a medium-to-high range of SNR, both the paper and simulation results confirm an identical trend that O-LSDC indeed decreases the BER. Although really low BER values at high SNR are analytical, the relative gain between schemes is still of value. This overlay of paper and simulation curves exhibits a good correspondence, further verifying the accuracy of the reliability modeling and SNR-to-BER mapping, despite the absolute BER values being only extrapolated. Indeed, O-LSDC provides large improvements in the BER, confirming the role of O-LSDC as a mechanism for increasing reliability.

4.7 O-LSDC Performance Gain Comparison

The third subplot shows the percentage performance increment of O-LSDC over the baseline scheme. This assumption is the reason for the better gains (up to ~11%)

at higher SNR values in the paper results whereas in our simulation we have only negative gains as we focus on throughput centric assumptions. In contrast, the latter emphasizes the need for assessing O-LSDC in realistic impairment dominated conditions, where its advantages become evident. The performance improvements of O-LSDC are scenario dependent with those advantages primarily becoming pronounced in reliability limited regimes.

4.8 Reliability: Target BER & SNR Gain.

In the fourth subplot, O-LSDC performs SNR reductions as targeted considering the fixed target BER. In order to achieve target BER of 10^{-7}, the paper claims an SNR gain of around 2.2 dB, while our anticipated values are lower but exhibit a similar behavior. The SNR gain increases to nearly 3 dB at more stringent reliability targets (10^{-9}). Such a reduction can be associated with an inherent transmit power reduction of 30–50%, which is of paramount importance in the context of ultra-reliable low-latency communication (URLLC) and energy-constrained 6G devices. O-LSDC is capable of robust transmission even when the SNR is extremely low.

4.9 Scenario-Based Performance Comparison

The fifth subplot compares the average spectral efficiency for different propagation scenarios. From the paper results, O-LSDC achieves the highest gains in THz indoor environments, up to 30%, followed by the urban micro and rural macro scenarios. This is again the same relative trend as in our simulation, but the values are lower in absolute value because we use simpler channel assumptions. O-LSDC performs especially well in THz and heavily disrupted propagation environments, where classical estimation fails.

4.10 6G KPI Projections Comparison

The last subplot is an overview of important 6G expectations such as maximum data rate, gain in capacity, and percentage of ideal capacity. The peak data rate gains, while small, are augmented by a considerable improvement in the share of capacity that can be achieved in scenarios where realistic signal processing and channel conditions are in place, thereby confirming O-LSDC as a reliability-enabling technology rather than a throughput-oriented design. O-LSDC enhances practical efficiency to within 6 to 18% of theoretical limits, despite only limited gains in absolute capacity.

5 Conclusion

In this paper, a comprehensive evaluation of the O-LSDC principles with multipurpose massive MIMO scenarios oriented towards 6G wireless communications was presented emphasizing on reliable performance against realistic channel conditions. The study showcased both attainable gains and realistic limitations of learning-assisted channel estimation by comparing published benchmark results to results from an independently developed simulation framework. O-LSDC, it is found, provides moderate improvements in spectral efficiency, typically 10–15% in favorable circumstances. Although the absolute capacity values differ due to different system assumptions and channel modeling, the trends confirm that O-LSDC is not a throughput oriented extension. Ultimately however, its clear edge is in facilitating accurate channel estimations. While the spectral efficiency gains of O-LSDC are modest under realistic 6G conditions, it achieves significant gains in terms of reliability, outage probability and power efficiency. These features impart O-LSDC attractive attributes for URLLC and THz-band applications, where the main design goal is not peak throughput rather it is robustness which is achieved by optimum combination of reliability, latency and spectral efficiency. Even more importantly, O-LSDC realizes significant reliability improvements, requiring 2–3 dB lower SNR than typical LS/MMSE-based methods to meet target bit error probabilities. This directly relates to lower transmit powers since the required SNR margin decreases, which in turn leads to more efficient and more robust transmission under channel impairments. In addition, outage probability analysis demonstrates that O-LSDC can yield up to one order of magnitude lower link outages as compared to the conventional techniques, especially in THz indoor and high-mobility scenarios where conventional techniques fail. In general, the results show that O-LSDC is reliability focused 6G enabler, enabling applications including ultra-reliable low-latency communication, and mission critical services in challenging propagation environments. Future research directions include the adoption of standardized 6G channel models, enhancing generalizability via advanced learning architectures, and validation performance under practical hardware and deployment constraints.

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