SRS-Based CSI Quality Assessment and Selection for MU-MIMO Precoding in 5G NR

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***Abstract*—Stable downlink precoding in time-division duplex (TDD) multi-user multi-input multi-output (MU-MIMO) systems critically depends on the reliability of channel state information (CSI) at the transmitter. In mobile environments, Doppler-induced channel variation, estimation noise, and pilot contamination distort the channel structure, often leading to ill-conditioned matrices and unstable linear precoding. This paper proposes a Doppler-aware CSI reliability framework in which the condition number of sounding reference signal (SRS)-based channel estimates is used as a per-snapshot indicator of spatial robustness. Instead of relying solely on instantaneous CSI, the proposed approach selects the better-conditioned CSI between current and previously estimated channel realizations prior to downlink transmission, thereby improving robustness under mobility. System-level simulations compliant with 5G New Radio specifications are conducted under fixed, increasing, and decreasing Doppler scenarios using clustered delay line (CDL) channel models. Results show consistent gains in throughput and block error rate (BLER), approaching the performance of the perfect channel state information at transmitter (CSIT). Among the considered schemes, regularized zero forcing (RZF) precoding exhibits higher robustness to CSI degradation, while block diagonalization (BD) is more sensitive to Doppler variations. Overall, the proposed method provides a lightweight and standard-compatible solution for improving MU-MIMO precoding reliability in time-varying channels.**

***Index Terms*—5G New Radio, MU-MIMO, channel state information (CSI), sounding reference signal (SRS), precoding.**

I. Introduction

THE evolution from fourth-generation (4G) LTE to fifth-generation new radio (5G NR) represents a fundamental redesign of the radio access network to support enhanced mobile broadband (eMBB), ultra-reliable low-latency communication (URLLC), and massive machine-type communications (mMTC). These requirements have driven the adoption of large antenna arrays and multi-user multiple-input multiple-output (MU-MIMO) transmission at the physical layer. In many deployments, time-division duplexing (TDD) is preferred due to its ability to exploit uplink (UL)–downlink (DL) reciprocity, enabling DL channel state information (CSI) acquisition from UL pilot signals without explicit feedback overhead [1], [2].

In 5G NR, sounding reference signals (SRS) are used to estimate UL channels, which are subsequently employed for DL MU-MIMO precoding and scheduling. The effectiveness of this approach depends critically on the accuracy and freshness of CSI at the time of transmission. Under user mobility, Doppler-induced channel variations cause CSI to age rapidly, making the coherence time a key limiting factor. Consequently, SRS periodicity introduces a fundamental tradeoff: dense sounding improves CSI accuracy but increases overhead, while sparse sounding reduces overhead at the risk of outdated CSI and degraded precoding performance [3], [4].

This challenge is particularly pronounced in MU-MIMO systems, where the performance of linear precoders such as zero-forcing (ZF), regularized ZF (RZF), and minimum mean-square error (MMSE) depends strongly on the conditioning of the multi-user channel matrix. Well-conditioned channels enable effective interference suppression and spatial multiplexing, whereas noise, pilot contamination, and Doppler-induced CSI aging can render the channel ill-conditioned. In such cases, linear precoders become numerically unstable, leading to residual interference, reduced throughput, and elevated block error rates (BLER) [3], [5].

Several techniques have been proposed to address CSI aging, including user grouping, adaptive SRS periodicity based on Doppler or time-domain channel properties, pilot design enhancements, and Doppler-aware CSI reuse mechanisms [6]. While these methods focus on deciding when to sound or how to allocate resources, they do not directly assess whether a given CSI snapshot is sufficiently reliable for MU-MIMO precoding at a particular instant. Existing CSI-aging mitigation approaches typically rely on channel prediction, interpolation, or adaptive sounding strategies, which may incur additional complexity under rapidly varying channel conditions.

Motivated by this gap, this paper proposes a Doppler-aware CSI reliability framework based on the condition number of SRS-estimated channel matrices. The condition number provides a compact scalar measure of spatial robustness, capturing the effects of Doppler-induced aging, pilot contamination, and noise, while directly relating to the numerical stability of linear precoders. By evaluating CSI quality on a per-snapshot basis, the proposed approach enables the selection of reliable CSI between current and previously estimated channel realizations, while preserving compatibility with standard SRS-based CSI acquisition procedures.

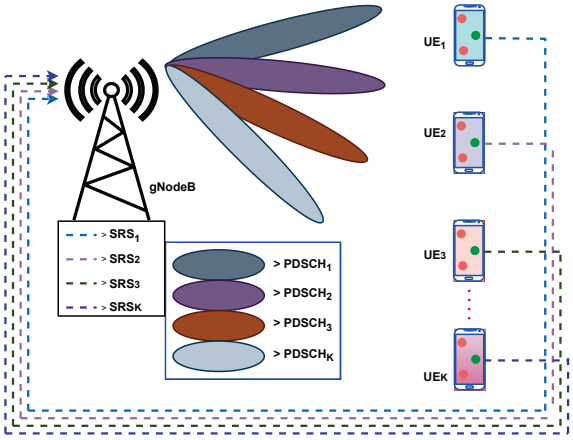


Figure 1: System model for SRS based channel estimation and DL precoding.

The main contributions of this work are summarized as follows:

- The condition number of SRS-estimated MU-MIMO channels is introduced as a per-snapshot reliability metric capturing the effects of Doppler aging, pilot contamination, and noise.
- A condition-number-based CSI selection mechanism is developed to retain the better-conditioned CSI realization for downlink precoding.
- The impact of CSI conditioning on the robustness of linear precoders, including ZF, RZF, and BD, is analyzed under varying Doppler regimes.
- The proposed framework is validated through 3GPP-compliant system-level simulations across multiple Doppler profiles, demonstrating consistent improvements in BLER and throughput, along with a reduced gap to the perfect channel state information at transmitter (CSIT).

Finally, while emerging waveforms such as orthogonal time-frequency space (OTFS) offer intrinsic Doppler robustness for beyond-5G systems, current 5G-Advanced and near-term deployments remain OFDM-based. Enhancing OFDM precoding reliability under high mobility therefore remains a critical requirement for standard-compliant networks.

II. System Model

We consider a TDD MU-MIMO downlink in 5G NR, where a gNB equipped with N_t transmit antennas serves K single-antenna UEs, as illustrated in Fig. 1. CSI is acquired at the gNB via uplink SRS, exploiting channel reciprocity for downlink precoding and user scheduling [3], [7], [8].

A. Channel Model with Doppler Aging

The downlink channel between the gNB and the k^{th} UE at SRS index n is modeled as

$$\mathbf{h}_k[n] \in \mathbb{C}^{1\times N_t}, \quad \mathbf{H}[n] = \begin{bmatrix} \mathbf{h}_1[n] \\ \vdots \\ \mathbf{h}_K[n] \end{bmatrix}, \tag{1}$$

where $\mathbf{h}_k[n]$ denotes the instantaneous complex channel vector from the N_t gNB antennas to the k^{th} UE , and $\mathbf{H}[n] \in \mathbb{C}^{K\times N_t}$ represents the composite MU-MIMO channel across all users.

The downlink channel is modeled using the 3GPP Clustered Delay Line (CDL) methodology. The channel coefficient between the s-th transmit antenna and the u-th receive antenna for the k-th user at time t is given by the superposition of L multipath rays:

$$h_{u,s,k}(t) = \sum_{l=1}^{L} \beta_{k,l}\, e^{j2\pi f_{D,k,l} t}\, e^{-j2\pi\tau_{k,l}B}\, a_{rx,k}(\phi_{k,l}^{\text{AOA}})\, a_{tx}(\phi_{k,l}^{\text{AOD}}), \tag{2}$$

where L is the number of rays (clusters), $\beta_{k,l}$ is the path gain, and $\tau_{k,l}$ is the path delay. The terms $a_{rx,k}(\cdot)$ and $a_{tx}(\cdot)$ denote the receive and transmit array response vectors for the angle of arrival (AOA) $\phi_{k,l}^{\text{AOA}}$ and angle of departure (AOD) $\phi_{k,l}^{\text{AOD}}$, respectively.

Unlike the statistical Jakes' model, the Doppler shift $f_{D,k,l}$ is explicitly modeled for each ray based on the user's velocity vector $\mathbf{v}_k$ and the spatial angle of arrival:

$$f_{D,k,l} = \frac{\mathbf{v}_k^T \cdot \mathbf{r}_{k,l}}{\lambda}, \tag{3}$$

where λ is the carrier wavelength and $\mathbf{r}_{k,l}$ is the unit vector in the direction of the l-th ray's arrival. This geometric modeling correctly captures the spatial consistency and directionality required for beamforming analysis in MU-MIMO systems.

Three Doppler scenarios are considered: (i) *fixed* Doppler (constant $f_{D,k}$), (ii) *increasing* Doppler (rising velocity and reduced coherence), and (iii) *decreasing* Doppler (lower velocity and improved channel stability). Multipath fading is modeled using the 3GPP CDL model [4], [9], [10] with delay profiles CDL-A through CDL-E.

B. Channel reciprocity under TDD

We consider a TDD system where the UL and DL channels are reciprocal. Assuming perfect calibration at the base station [10], the UL channel is modelled as the transpose of the DL channel

$$\mathbf{H}_{\text{UL}} = \mathbf{H}_{\text{DL}}^{\text{T}} \tag{4}$$

consistent with the 3GPP channel modelling guidelines [11].

C. CSI Acquisition via SRS

Each UE transmits an orthogonal SRS sequence $s_k[m]$ across selected subcarriers m. The received pilot signal at the gNB is modeled as

$$\mathbf{Y} = \mathbf{H}_{\text{UL}}\mathbf{S} + \mathbf{N}, \tag{5}$$

where $\mathbf{Y} \in \mathbb{C}^{N_t\times M}$ denotes the received SRS matrix, $\mathbf{S} \in \mathbb{C}^{K\times M}$ contains transmitted pilot symbols across M subcarriers, and $\mathbf{N}$ is additive white Gaussian noise (AWGN). Here, $\mathbf{Y}$ is expressed in the frequency domain, assuming per-subcarrier orthogonal pilot transmission as in OFDM-based SRS design. The underlying time-domain convolution between the channel impulse response and transmitted signal

is implicitly absorbed into the frequency response $\mathbf{H}$. This formulation aligns with 5G NR specifications for SRS-based channel estimation [8], [12].

A least-squares (LS) estimate of the channel is then obtained as

$$\widehat{\mathbf{H}}_{\mathrm{LS}} = \mathbf{Y}\mathbf{S}^{\dagger}, \tag{6}$$

where $(\cdot)^{\dagger}$ denotes the Moore–Penrose pseudo-inverse and with received pilot signal ($\mathbf{Y}$) at the gNB and the pilot matrix ($\mathbf{S}$), the resulting estimate $\widehat{\mathbf{H}}_{\mathrm{LS}}$ yields dimension $\mathbf{N_t} \times \mathbf{K}$, which correctly captures the channel state for all antennas. This ensures the system is fully determined provided $\mathbf{M} \geqslant \mathbf{K}$. Limited orthogonal SRS resources may force sequence reuse among UEs, introducing *pilot contamination* that degrades channel estimation accuracy [3], [5], [12].

D. Condition Number as a CSI-Quality Metric

To assess the reliability of the estimated channel, the gNB computes the condition number of $\widehat{\mathbf{H}}[n]$ as

$$\kappa(\widehat{\mathbf{H}}[n]) = \sqrt{\frac{\lambda_{\max}(\widehat{\mathbf{H}}[n]\widehat{\mathbf{H}}^{H}[n])}{\lambda_{\min}(\widehat{\mathbf{H}}[n]\widehat{\mathbf{H}}^{H}[n])}}, \tag{7}$$

where $\lambda_{\max}(\cdot)$ and $\lambda_{\min}(\cdot)$ denote the largest and smallest eigenvalues, respectively. A low κ indicates a well-conditioned channel with orthogonal spatial modes, while a high κ signals correlated or noisy CSI, leading to unstable precoding [13], [14].

To improve numerical robustness, a regularized condition number [15], [16] is employed:

$$\widehat{\kappa}_{\delta} = \sqrt{\frac{\lambda_{\max}(\mathbf{G}[n] + \delta I)}{\lambda_{\min}(\mathbf{G}[n] + \delta I)}}, \quad \mathbf{G}[n] = \widehat{\mathbf{H}}[n]\widehat{\mathbf{H}}^{H}[n], \tag{8}$$

where $\delta > 0$ is a small regularization constant and I is the $K \times K$ identity matrix. This ridge-like regularization stabilizes eigenvalue ratios and mitigates CSI degradation due to Doppler or pilot contamination. The additional computational overhead is limited to condition-number evaluation of a small Gram matrix and is negligible compared with the matrix inversion operations already required by linear precoders.

E. CSI Reliability Filtering Rule

At each SRS instance n, the gNB evaluates the reliability of the estimated CSI snapshot $\hat{\mathbf{H}}[n]$ using the regularized condition number ($\hat{\kappa}_{\delta}[n]$), where larger values indicate poorer channel conditioning and increased sensitivity of linear precoders to channel aging, noise, and pilot contamination.

The retained CSI is updated according to

$$\hat{\mathbf{H}}^{\star}[n] = \begin{cases} \hat{\mathbf{H}}[n], & \hat{\kappa}_{\delta}[n] < \hat{\kappa}_{\delta}[n-1], \\ \hat{\mathbf{H}}[n-1], & \text{otherwise}, \end{cases} \tag{9}$$

The newly estimated CSI is retained only when it exhibits improved channel conditioning. For initialization, the first valid CSI estimate is retained as the reference CSI. Consequently, a single retained CSI realization is maintained in memory and updated only when a better-conditioned estimate becomes available.

This lightweight reliability check operates entirely at the gNB without modifying the standard 3GPP NR SRS transmission procedure. By retaining the better-conditioned CSI realization, the framework improves precoding robustness under time-varying Doppler conditions.

F. Downlink Precoding and Received Signal

In this work, three linear precoding schemes are considered. ZF suppresses inter-user interference through channel inversion, RZF improves robustness by incorporating a regularization term during inversion, and BD employs null-space projections to mitigate inter-user interference among scheduled users. Using the selected CSI $\widehat{\mathbf{H}}^{\star}[n]$, the gNB computes the ZF precoder:

$$\mathbf{W}[n] = \widehat{\mathbf{H}}^{\star H}[n](\widehat{\mathbf{H}}^{\star}[n]\widehat{\mathbf{H}}^{\star H}[n])^{-1}. \tag{10}$$

The received signal for the k^{th} UE is

$$y_k = \mathbf{h}_k[n]\mathbf{w}_k[n]x_k + \sum_{j \neq k} \mathbf{h}_k[n]\mathbf{w}_j[n]x_j + z_k, \tag{11}$$

where $\mathbf{w}_k$ is the k-th column of $\mathbf{W}$, x_k is the transmitted symbol for the k^{th} UE, and $z_k \sim \mathcal{CN}(0, \sigma^2)$ is AWGN. The first term denotes the desired signal, and the second represents residual multiuser interference.

The instantaneous signal-to-interference-plus-noise ratio (SINR) for the k^{th} UE is given by

$$\gamma_k = \frac{|\mathbf{h}_k[n]\mathbf{w}_k[n]|^2}{\sum_{j \neq k}|\mathbf{h}_k[n]\mathbf{w}_j[n]|^2 + \sigma^2}, \tag{12}$$

which reflects the received signal quality after precoding and interference suppression [14].

G. Performance Metrics

The BLER and throughput for the k^{th} UE are defined as

$$\mathrm{BLER}_k = \frac{E_k}{N_k}, \quad R_k = \frac{(1 - \mathrm{BLER}_k)\, B_{\mathrm{RB}} \log_2(1 + \gamma_k)}{T}, \tag{13}$$

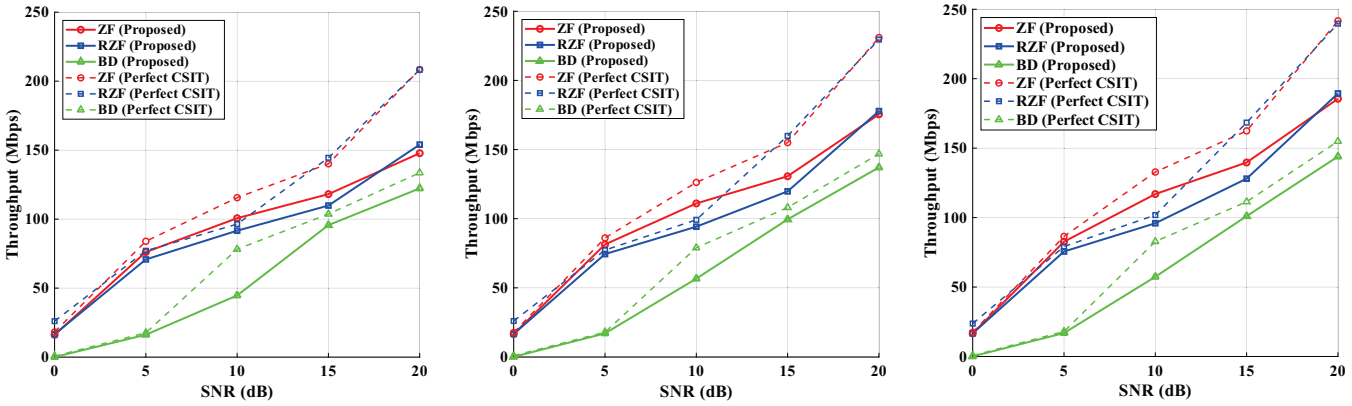
where E_k and N_k denote the number of erroneous and total transmitted blocks, respectively; B_{RB} is the allocated bandwidth per resource block; γ_k is the effective SINR; and T is the slot duration. The aggregate throughput and average BLER are computed as

$$R_{\mathrm{sum}} = \sum_{k=1}^{K} R_k, \quad \mathrm{BLER}_{\mathrm{avg}} = \frac{1}{K}\sum_{k=1}^{K} \mathrm{BLER}_k. \tag{14}$$

These metrics, consistent with 3GPP link-level evaluation procedures [12], are used to assess the impact of Doppler variation, delay spread, and CSI quality on MU-MIMO downlink performance.

III. Simulation Setup

The simulations are performed in MATLAB using a 3GPP-compliant 5G NR MU-MIMO TDD system with 1000 Monte Carlo trials. Downlink precoding is derived from uplink SRS measurements through channel reciprocity. The key simulation parameters are summarized in Table I. A $4\times4\times2$ uniform



(a) (b) (c)

Figure 2: Throughput performance of various precoding methods across different Doppler scenarios: (a) Increasing Doppler shift, (b) Fixed Doppler shift, and (c) Decreasing Doppler shift.

planar array (UPA) at the gNB serves four UEs over a 3GPP CDL channel with 100 ns delay spread. Fixed, increasing, and decreasing Doppler scenarios are considered to evaluate mobility effects. The performance of ZF, RZF, and BD precoding schemes is assessed in terms of throughput and BLER. Although BD provides lower throughput than ZF and RZF in the considered scenarios, it is included as a representative MU-MIMO precoding benchmark for evaluating the proposed CSI-reliability framework across different linear precoding strategies.

Table I: Simulation Parameters

Parameter	**Value**
Carrier bandwidth	64 PRBs ($\approx$ 20 MHz at 30 kHz SCS)
SCS	30 kHz
Frame structure	TDD, cyclic pattern [D, D, D, D, D, D, D, S, U, U]
Special slot structure	[6 DL, 4 GP, 4 UL] OFDM symbols
Number of frames	2 (20 slots/frame at 30 kHz SCS)
BS antenna array	$4 \times 4 \times 2$ (rows $\times$ columns $\times$ polarizations)
Number of UEs	4
UE antenna configuration	Adaptive (1×1 up to 2×2)
Number of spatial groups	6 (JSDM-based grouping)
Scheduled DL layers	8
Channel model	3GPP CDL-A, delay spread = 100 ns
Doppler shift	Decreasing: [17.5, 15.5, 14.5, 13.5] Hz ($\approx$ 5–4 km/h) Fixed case: 17.5 Hz Increasing: [17.5, 20.5, 25.5, 26.5] Hz
Uplink SNR	18 dB
Downlink SNR sweep	5:5:20 dB
Precoding methods	ZF, RZF, BD
Channel estimation	Uplink SRS-based, imperfect CSI
Performance metrics	Data rate (Mbps), BLER

IV. RESULTS AND DISCUSSIONS

We now present system-level simulation results of the proposed Doppler-aware CSI selection framework under different precoding schemes: ZF, RZF, and BD. Unless specified, results are averaged over multiple channel realizations. We evaluate throughput and BLER as functions of DL SNR under fixed, increasing, and decreasing Doppler scenarios.

Increasing Doppler: Fig. 2a shows that performance degrades under increasing Doppler due to channel aging, which reduces the accuracy of SRS-based CSI used for downlink precoding. Unlike the perfect CSIT baseline, where the channel is assumed to be perfectly known at the transmitter, practical SRS-based CSI introduces a noticeable deviation from ideal performance.

In contrast, the proposed method selects the better-conditioned CSI between the current and previously estimated channel realizations. At 20 dB, this results in a throughput of 147.8 Mbps, closely tracking ZF and RZF, while BD achieves significantly lower performance. More importantly, the proposed method maintains a smaller gap to the perfect CSIT baseline.

The BLER results follow a similar trend. The proposed method achieves 0.463, comparable to ZF/RZF and lower than BD, while remaining closer to the perfect CSIT curve. This confirms that the proposed selection mechanism effectively mitigates CSI degradation under fast channel variations.

Fixed Doppler: Under fixed Doppler (Figs. 2b, 3b), the channel varies slowly, improving CSI reliability. As a result, the deviation from the perfect CSIT baseline reduces for all schemes.

At 20 dB, the proposed method achieves 175.5 Mbps, closely matching ZF/RZF and outperforming BD. The gap to the perfect CSIT baseline is further reduced compared to the increasing Doppler case. BLER also improves to 0.374, aligning with ZF/RZF and remaining closer to the ideal performance than BD. This demonstrates that the proposed method effectively preserves reliable CSI under stable channel conditions.

Decreasing Doppler: For decreasing Doppler (Figs. 2c, 3c), channel conditions gradually improve, increasing coherence time and enhancing CSI accuracy. In this scenario, the proposed method efficiently exploits previously estimated CSI when it is better conditioned than the current estimate.

At 20 dB, the proposed method achieves 185.6 Mbps, closely following ZF/RZF and maintaining a reduced gap to the perfect CSIT baseline. BD continues to show lower per-

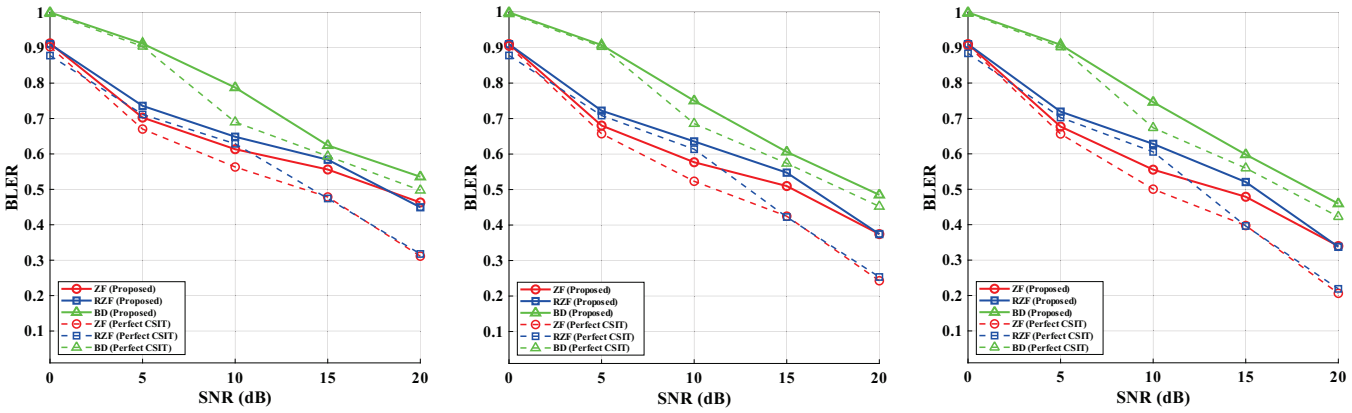


Figure 3: BLER performance of various precoding methods across different Doppler scenarios: (a) Increasing Doppler shift, (b) Fixed Doppler shift, and (c) Decreasing Doppler shift.

formance. BLER improves to 0.340, comparable to ZF/RZF and closer to the ideal case than BD.

Across all Doppler scenarios, the proposed method consistently reduces the gap between practical CSI-based performance and the perfect CSIT baseline, where the channel is assumed to be perfectly known at the transmitter. This improvement is most significant under increasing Doppler, where CSI degradation is severe. Overall, the results confirm that selecting well-conditioned CSI enables more reliable precoding and performance closer to the ideal case.

V. Conclusion

This paper proposes a Doppler-aware CSI reliability framework for TDD MU-MIMO systems, where the condition number of SRS-based channel estimates is used to select the most reliable CSI for transmission. By choosing between instantaneous and previously estimated CSI, the proposed method mitigates the effects of channel aging, noise, and estimation errors under mobility. Simulation results in a 5G NR-compliant setup show consistent improvements in throughput and BLER across varying Doppler scenarios compared to conventional approaches that rely solely on instantaneous CSI. The proposed method maintains a smaller gap to the perfect CSIT, particularly in fast-varying channels where CSI degradation is significant. Among the precoding schemes, RZF demonstrates higher robustness, while BD remains more sensitive to CSI imperfections. Overall, the proposed approach provides a simple and standard-compatible solution to enhance MU-MIMO reliability under practical mobility conditions. Future work will focus on adaptive threshold design for CSI selection and extensions to multi-cell and coordinated MU-MIMO systems.

Acknowledgment

This work was supported by Rakuten Mobile, Inc., Setagaya, Tokyo, Japan.

References

[1] Q. Xue, C. Ji, S. Ma, J. Guo, Y. Xu, Q. Chen, and W. Zhang, "A survey of beam management for mmwave and THz communications towards 6G," *IEEE Commun. Surveys Tuts.*, vol. 26, no. 3, pp. –, 2024.

[2] M. Giordani, M. Polese, A. Roy, D. Castor, and M. Zorzi, "A tutorial on beam management for 3GPP NR at mmwave frequencies," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 1, pp. –, 2019.

[3] A. Kalachikov and A. Stenin, "Performance evaluation of the srs-based mimo channel estimation on 5G NR open source channel model," in *Proc. IEEE Int. Conf. Young Prof. Electron Devices Mater. (EDM)*, 2021.

[4] P. Chaki, J. Shikida, and K. Muraoka, "Resource allocation for sounding reference signal in 5g massive mimo under channel aging," in *Proc. IEEE Globecom Workshops (GC Wkshps)*, 2024.

[5] Q. Zhang, Y. Chang, and T. Zeng, "Srs-limited user grouping scheduling algorithm for downlink massive mimo systems," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, 2019.

[6] L. K. Bharti, A. Ravi, K. Venkataraghvan, and P. Kumar, "Srs-aided channel estimation and doppler-adaptive csi reuse for 5g nr mu-mimo: A slot-level performance evaluation," in *2026 National Conference on Communications (NCC)*, 2026, pp. 543–548.

[7] J.-Y. Baek, E.-K. Hong, and G. Kaddoum, "A study on channel estimation algorithm with sounding reference signal for tdd downlink scheduling," in *Proc. IEEE Veh. Technol. Conf. (VTC-Fall)*, 2017.

[8] 3GPP, "NR; Physical Channels and Modulation, 3GPP TS 38.211, Release 18," 3rd Generation Partnership Project (3GPP), Tech. Rep., 2025.

[9] G. Jiang, B. Gao, M. Mei, M. Zou, X. Guo, and R. Li, "Srs periodicity determination aided by time-domain channel property," in *Proc. IEEE Globecom Workshops (GC Wkshps)*, 2024, pp. –.

[10] 3GPP, "Study on Channel Model for Frequencies from 0.5 to 100 GHz, 3GPP TR 38.901, Release 17," 3rd Generation Partnership Project (3GPP), Tech. Rep., 2022.

[11] T. L. Marzetta, "Non cooperative cellular wireless with unlimited numbers of base station antennas," *IEEE Transactions on Wireless Communications*, vol. 9, no. 11, pp. 3590–3600, Nov. 2010.

[12] 3GPP, "NR; Physical Layer Procedures for Data, 3GPP TS 38.214, Release 15," 3rd Generation Partnership Project (3GPP), Tech. Rep., 2019.

[13] K.-Y. Lee, Y.-J. Song, and J.-S. Jang, "Adaptive downlink beamforming based on srs for channel estimation using coherence bandwidth characteristic in sub-6 ghz 5g nr," in *Proc. IEEE Wireless Telecommun. Symp. (WTS)*, 2021.

[14] J. Zhang, J. G. Andrews, R. W. Heath, and A. Lozano, "Analysis of multiuser mimo with regularized zero-forcing precoding," *IEEE Trans. Wireless Commun.*, vol. 9, no. 11, pp. 3655–3665, 2010.

[15] A. E. Hoerl and R. W. Kennard, "Ridge regression: Biased estimation for nonorthogonal problems," *Technometrics*, vol. 12, no. 1, pp. 55–67, 1970.

[16] G. H. Golub and C. F. V. Loan, *Matrix Computations*, 4th ed. Baltimore, MD: Johns Hopkins Univ. Press, 2013.