

Low-Complexity RIS-Aided MISO–LoRa for IIoT via Equivalent Channel Estimation and Codebook Optimization

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Abstract—Industrial Internet of Things (IIoT) networks operating in indoor non-line-of-sight (NLoS) environments suffer from severe reliability degradation due to blockage, multipath propagation, and low signal-to-noise ratio (SNR), particularly in low-power long-range (LoRa) systems. Existing reconfigurable intelligent surface (RIS)-assisted solutions generally require separate estimation of the Tx–RIS and RIS–Rx channels followed by iterative phase optimization, leading to substantial training overhead and computational complexity. To address these limitations, this paper proposes a low-complexity RIS-assisted multiple-input single-output (MISO) LoRa framework based on direct estimation of an equivalent end-to-end channel, thereby avoiding individual link estimation and cascaded channel state information (CSI) reconstruction. The proposed framework operates in two stages. First, a scalar equivalent channel is estimated using a linear minimum mean square error (LMMSE) estimator under low-SNR conditions. Second, a low-complexity codebook-based RIS configuration scheme selects the quantized phase profile that maximizes the estimated equivalent channel gain. Simulation results demonstrate significant reliability improvements over conventional LoRa systems and random RIS configurations. For $N = 16$ RIS elements, the proposed approach achieves an SNR gain of approximately 8 dB at a bit error rate (BER) of 10^{-4} . Furthermore, performance improves with increasing RIS size and number of transmit antennas, highlighting the scalability and practical suitability of the proposed framework for IIoT deployments.

I. INTRODUCTION

Long range (LoRa), the physical layer technology underpinning the LoRa wide area network (LoRaWAN) protocol developed by Semtech [1], has emerged as one of the most widely adopted low-power wide area network (LPWAN) technologies for the internet of things (IoT). Its capability to support long-range connectivity while maintaining ultra-low power consumption makes it particularly attractive for a wide range of IoT applications. However, LoRa systems face significant challenges in industrial IoT (IIoT) environments, where harsh propagation conditions, including severe non-line-of-sight (NLoS) scenarios, heavy multipath fading, and strong signal attenuation, may substantially degrade link reliability. To address these challenges, recent studies have explored the integration of multiple antennas at the transmitter and/or re-

ceiver in LoRa systems, leading to what is commonly referred to as multiple-input multiple-output (MIMO)-LoRa. These approaches aim to enhance link reliability and robustness by leveraging spatial diversity to mitigate fading and improve communication stability in challenging wireless environments. For example, in [2], a precoding scheme was proposed to maximize the received signal-to-noise ratio (SNR), thereby improving the bit error rate (BER) performance.

However, in industrial environments with severe blockage and rich multipath propagation, spatial diversity alone may be insufficient to ensure reliable communication. To enhance link robustness, this paper investigates the integration of reconfigurable intelligent surface (RIS) into a MISO-LoRa framework. By adjusting the phase shifts of its passive elements, the RIS enables control of the propagation environment, creates additional constructive paths, and improves received signal power under adverse conditions. RIS are programmable electromagnetic surfaces that enhance wireless communication by dynamically reconfiguring the propagation environment [4]. RIS technology is gaining increasing attention in both academic and industrial circles, offering vast potential applications and including enhancements like expanding network coverage, increasing efficiency in wireless spectrum use, minimizing power consumption during data transmission, improving over-the-air computational performance, and enabling secure wireless communication [5]. Additionally, due to its promising characteristics, RIS technology has attracted substantial research interest in MIMO-based wireless communication systems. The accuracy of the channel state information (CSI) available at the terminals significantly influences the BER performance of RIS-assisted MIMO systems [6]. Moreover, the design of RIS phase shifts is critical to ensuring effective signal enhancement. In [7], the access point jointly optimizes the RIS phase shifts and the transmit beamforming vector to maximize the received signal power. Furthermore, [8] proposes an alternating optimization (AO) algorithm that jointly optimizes the RIS phase shifts and the linear receive filter under the minimum mean square error (MMSE) criterion, ensuring convergence to an optimal solution.

Recent advances in lightweight and energy-efficient RIS architectures, specifically designed for low-complexity IoT applications [9]–[10], have demonstrated the practical feasibility of deploying RIS in industrial and smart IoT environments. These developments indicate that RIS technology can effectively enhance wireless coverage, improve link reliability, and support low-power long-range communications, making it a promising solution for LoRa-based IIoT systems.

Despite these promising advantages, the integration of RIS with LoRa communication systems remains relatively under-explored. In [11], the authors investigate the combination of RIS and LoRa modulation and highlight its potential to improve system performance and increase achievable data rates. Similarly, [12] studies a RIS-assisted LoRa system under co-spreading factor (co- SF) interference in Nakagami- m fading channels, considering both coherent and non-coherent detection schemes. Their results show that RIS can effectively optimize the propagation environment and mitigate interference, thereby enhancing overall system performance. However, these works do not address the optimization of RIS phase shifts, which is a critical factor for fully exploiting the performance gains of RIS-assisted LoRa systems. In our previous work [13], we proposed a RIS-assisted LoRa architecture incorporating an ultra-lightweight channel estimation method and a low-complexity gradient-based phase-shift optimization algorithm. Simulation results demonstrated significant BER improvements compared to conventional LoRa systems under additive white Gaussian noise (AWGN) conditions. Building on this work, our research group further investigated discrete RIS phase-shift optimization [14]. While exhaustive search was employed for small RIS deployments, a genetic algorithm (GA) was adopted for larger RIS configurations to reduce computational complexity while maintaining high performance. These studies highlighted the importance of low-complexity RIS optimization techniques for resource-constrained IoT networks.

The main contributions of this paper are summarized as follows:

- **Equivalent Channel Estimation Framework without Cascaded CSI:**

An equivalent channel estimation framework is developed for RIS-assisted MISO-LoRa systems, in which the scalar end-to-end channel coefficient is directly estimated from pilot observations, avoiding individual or cascaded channel estimation. An LMMSE estimator is employed as a benchmark linear estimator within the proposed framework, while the main contribution lies in the equivalent-channel estimation framework rather than in the underlying estimation algorithm.

- **Discrete Codebook-Based RIS Configuration Strategy:**

We develop a low-complexity RIS phase selection method based on a predefined discrete codebook and the estimated equivalent channel. The optimal configuration is selected by maximizing the received signal gain, avoiding iterative optimization and full CSI acquisition.

- **Comprehensive Performance Evaluation under Practical IIoT Constraints:** Through extensive Monte Carlo simulations under realistic fading and shadowing conditions, we demonstrate that the proposed framework significantly improves BER performance compared to conventional LoRa and benchmark RIS-assisted schemes, while ensuring scalability with respect to RIS size and transmit diversity under low-SNR conditions.

The remainder of this paper is organized as follows. Section II reviews the conventional LoRa communication system. Section III describes the proposed RIS-assisted MISO-LoRa architecture for IIoT applications. Section IV presents the equivalent channel estimation procedure used for RIS optimization. Section V introduces the low-complexity codebook-based RIS phase optimization algorithm relying on quantized discrete phase shifts. Section VI analyzes the BER performance through Monte Carlo simulations under realistic low-SNR conditions. Finally, Section VII concludes the paper and discusses future research directions.

Notations : We use $(\cdot)^T$, $(\cdot)^H$, and $(\cdot)^*$ to denote the transpose, Hermitian (conjugate transpose), and complex conjugate operations, respectively. The symbol j represents the imaginary unit, i.e., $j = \sqrt{-1}$.

II. CONVENTIONAL LORA SYSTEM MODEL

A conventional LoRa wireless architecture comprises three primary components: the LoRa device (transmitter), the LoRa gateway (receiver), and the LoRa network server. Communication occurs over the air via LoRa radio signals, transmitted from the RF front-end of the device to the RF receiver at the gateway, enabling bidirectional communication through the LoRaWAN protocol stack. LoRa operates at the physical (PHY) layer and employs M-ary frequency shift keying (M-FSK) modulation combined with chirp spread spectrum (CSS), where each symbol is represented by a chirped waveform—i.e., a signal whose frequency varies linearly over time [15]. Two types of chirps are typically used: up chirps, where frequency increases over time, and down chirps, where it decreases. LoRa supports three configurable bandwidths, $B_w \in \{125 \text{ kHz}, 250 \text{ kHz}, 500 \text{ kHz}\}$, offering a trade-off between data rate and transmission range.

We consider a sequence of B independent and identically distributed (i.i.d.) bits. The bitstream is segmented into words of SF bits, where each word is mapped to a symbol from the set $\mathcal{A} = \{0, M-1\}$, with $M = 2^{SF}$. The SF is chosen from the set $\{7, 8, 9, 10, 11, 12\}$ [15].

The transmitted signal is expressed as

$$S(t) = \sum_{m=0}^{B/SF} w_{s_m}(t - m T_s). \quad (1)$$

$$w_s(t) = \begin{cases} e^{j(2\pi(f_c + \frac{\gamma_s}{T_s})t + 2\pi\frac{\gamma}{2}(t - \frac{T_s}{2})^2)} & \text{if } 0 \leq t \leq (1 - \frac{s}{M})T_s, \\ e^{j(2\pi(f_c - \frac{B_{\text{BW}}}{2})t + 2\pi\frac{\gamma}{2}(t - (1 - \frac{s}{M})T_s)^2)} & \text{if } (1 - \frac{s}{M})T_s < t \leq T_s, \end{cases} \quad (2)$$
$$\gamma = \frac{f_{max} - f_{min}}{T_s} = \frac{B_w}{T_s}, \quad (3)$$

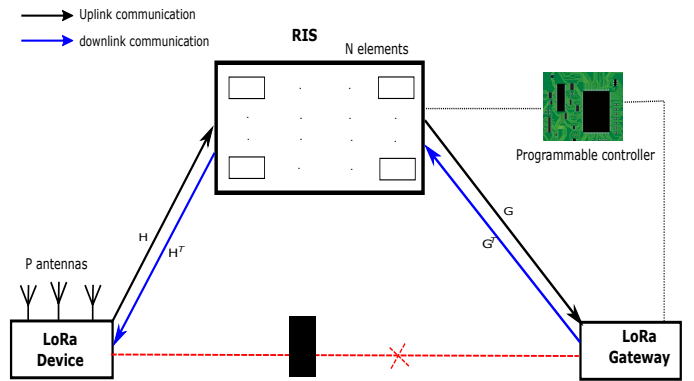
In IIoT networks, the received signal can be modeled as:

where $n(t) \sim \mathcal{CN}(0, N_0)$ denotes AWGN with power spectral density N_0 , and $h(t)$ represents the impulse response of the channel between the device and the gateway, given by

where A_l and θ_l denote the attenuation and delay of the l^{th} path, respectively, L is the number of propagation paths, and $\delta(\cdot)$ is the Dirac delta function. Although industrial LoRa channels exhibit multipath propagation, a narrowband flat-fading model is assumed since the LoRa bandwidth is much smaller than the channel coherence bandwidth.

A. System Design

During uplink transmission, the transmitted signal is reflected by the RIS toward the gateway. The RIS phase shifts are assumed to be configurable to enhance the received signal quality by enabling constructive combining of the reflected paths. While this work focuses on uplink transmission, the proposed framework can be extended to downlink operation under time-division duplexing (TDD) by exploiting channel reciprocity. Let $\mathbf{H} \in \mathbb{C}^{N \times P}$ and $g \in \mathbb{C}^{N \times 1}$ denote the baseband-equivalent Rayleigh fading channels between the LoRa device and the RIS, and between the RIS and the LoRa gateway, respectively. A unit-norm precoding vector



$w \in \mathbb{C}^{P \times 1}$ is employed at the transmitter for beamforming. The received signal at the gateway is expressed as:

where P_t denotes the transmit power, and $S(t)$ is the transmitted LoRa signal. The RIS reflection matrix is defined as

where ϕ_i denotes the phase shift applied by the i^{th} RIS element. In this work, a unit-modulus reflection model is adopted, where each RIS element adjusts only the phase of the incident signal while maintaining a constant reflection amplitude. Due to practical hardware constraints, the phase shifts are implemented using finite-resolution phase shifters. Specifically, a 2-bit quantization model is considered, resulting in four discrete phase states given by

$$\phi_i \in \mathcal{Q} = \left\{0, \frac{\pi}{2}, \pi, \frac{3\pi}{2}\right\}. \quad (8)$$

This quantization scheme provides four uniformly spaced phase states over the interval $[0, 2\pi)$ and is widely adopted in low-complexity and cost-effective RIS implementations. The RIS phase vector is defined as

$$\phi = [\phi_1, \phi_2, \dots, \phi_N]^T, \quad (9)$$

which uniquely determines the reflection matrix Φ .

B. Problem Formulation

Unlike conventional wireless systems, where sum-rate maximization is typically considered as the primary optimization objective [5], LoRa-based IIoT networks prioritize communication reliability over spectral efficiency. This is due to operation under strict power constraints and fixed transmission parameters, namely the SF and B_w , which inherently limit the achievable data rate. In LoRa systems, non-coherent CSS modulation is employed for signal detection. In low-SNR IIoT environments, channel impairments mainly degrade the effective received SNR, which directly impacts CSS detection reliability. Therefore, maximizing the received signal power is

adopted as a surrogate objective for BER minimization, and the RIS phase-shift optimization problem is formulated as

$$\phi^{\text{opt}} = \arg \max_{\phi} |g^H \Phi \mathbf{H} w|^2. \quad (10)$$

Direct BER optimization is avoided due to the highly non-linear and non-convex relationship between RIS phase shifts and CSS detection performance. The transmit beamforming vector is assumed fixed and independent of RIS optimization, avoiding joint optimization and reducing computational complexity, making the design suitable for resource-constrained IoT devices. A two-stage framework is adopted, where channel estimation is first performed (as detailed in the following section), followed by RIS phase-shift optimization based on the estimated equivalent channel.

IV. CHANNEL ESTIMATION

Accurate channel estimation is essential for RIS-assisted LoRa-based IIoT systems operating in harsh industrial environments under severe low-SNR conditions. Due to the limited transmit power of LoRa devices and strong attenuation caused by blockage and multipath propagation, reliable channel acquisition is critical for robust communication. During the training phase, a predefined RIS codebook containing K reflection configurations is employed. Each configuration $\Phi^{(k)}$ is sequentially activated while pilot symbols are transmitted. Instead of separately estimating the Tx–RIS and RIS–Rx channels, the proposed framework directly estimates an equivalent end-to-end scalar channel for each RIS state. This reduces the estimation problem from high-dimensional channel matrices ($N \times P$ and $N \times 1$) to a single scalar coefficient, significantly reducing CSI dimensionality and computational complexity. Since the transmit beamforming vector is fixed during training, the equivalent channel is expressed as

$$c^{(k)} = g^H \Phi^{(k)} \mathbf{H} w, \quad (11)$$

where $k \in \{1, \dots, K\}$ denotes the RIS configuration index.

For each configuration, M_s pilot symbols $s \in \mathbb{C}^{M_s \times 1}$ with $\|s\|^2 = M_s$ are transmitted. The received signal is

$$y^{(k)} = s c^{(k)} + n, \quad (12)$$

where $n \sim \mathcal{CN}(\mathbf{0}, N_0 \mathbf{I})$. Since the RIS only changes the phase of the reflected signals without affecting their amplitudes, the channel variance is assumed approximately constant across different RIS configurations.

The LS estimate is given by [16]

$$\hat{c}_{\text{LS}}^{(k)} = \frac{1}{M_s} s^H y^{(k)}. \quad (13)$$

The equivalent channel coefficient is modeled as

$$c^{(k)} \sim \mathcal{CN}(0, \sigma_c^2), \quad (14)$$

where the large-scale fading remains constant across RIS states. For moderate-to-large RIS dimensions, the equivalent channel can be reasonably approximated as a complex Gaussian random variable owing to the aggregation of a

large number of reflected components undergoing independent small-scale fading. The equivalent scalar channel captures the effective end-to-end Tx–RIS–Rx response for each RIS configuration. Under this assumption, the LMMSE estimator is given by [16]

$$\hat{c}_{\text{LMMSE}}^{(k)} = \frac{\sigma_c^2}{\sigma_c^2 M_s + N_0} s^H y^{(k)}. \quad (15)$$

Unlike conventional approaches based on individual Tx–RIS and RIS–Rx channel estimation, the proposed method directly estimates a scalar equivalent channel, avoiding high-dimensional matrix operations. Consequently, the LS and LMMSE estimators require only vector inner products, resulting in a linear complexity of $O(M_s)$ per RIS configuration. The estimation performance is evaluated using the mean square error (MSE) [17]

$$\text{MSE} = \mathbb{E} \left[|\hat{c}^{(k)} - c^{(k)}|^2 \right], \quad (16)$$

which quantifies the average distortion between the true equivalent channel and its estimate, and directly reflects the accuracy of the channel acquisition process. Although closed-form MSE expressions exist for both LS and LMMSE estimators, Monte Carlo simulations are additionally conducted to validate the analytical behavior under randomly generated channel and noise realizations. The MSE is therefore approximated as

$$\text{MSE} \approx \frac{1}{N_{\text{MC}}} \sum_{i=1}^{N_{\text{MC}}} \left| \hat{c}^{(k,i)} - c^{(k,i)} \right|^2, \quad (17)$$

with $N_{\text{MC}} = 5000$ independent channel realizations to ensure statistical reliability of the results. The system is evaluated over an SNR range of -30 dB to 10 dB with a pilot length of $M_s = 128$ symbols. This operating range is chosen to reflect realistic low-power LoRa-based IIoT deployments in harsh industrial environments, where received signals are typically noise-limited. “Fig. 2” illustrates that the LMMSE estimator consistently outperforms the LS estimator in the low-SNR regime (-30 dB to -15 dB), where noise dominates the received signal. This gain is attributed to the exploitation of second-order channel statistics, which enables more effective noise suppression compared to the purely data-driven LS approach. As the SNR increases, the effect of noise diminishes, and both estimators converge toward similar performance in the high-SNR regime. These results validate the effectiveness of the proposed equivalent-channel estimation framework for RIS-assisted LoRa-based IIoT systems, while maintaining very low computational complexity and making it well-suited for resource-constrained industrial IoT devices. The estimated equivalent channel coefficients are subsequently utilized for RIS configuration selection, as described in the following section.

V. OPTIMIZATION RIS PHASE SHIFTS

A codebook-based RIS phase selection strategy is adopted, where the optimal configuration is chosen from a predefined

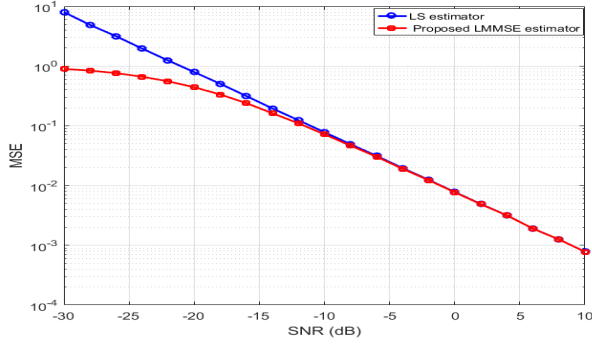


Fig. 2: MSE performance versus SNR.

set without iterative optimization. Each RIS element selects its phase from a discrete set $\mathcal{Q}$ [18], leading to the codebook

$$\mathcal{P} = \left\{ \Phi^{(1)}, \dots, \Phi^{(K)} \right\}, \quad (18)$$

generated via uniform phase quantization. Each configuration is defined as

$$\Phi^{(k)} = \text{diag} \left(e^{j\phi_1^{(k)}}, \dots, e^{j\phi_N^{(k)}} \right), \quad (19)$$

with $\phi_n^{(k)} \in \mathcal{Q}$. Using the estimated equivalent channel $\hat{c}^{(k)}$ obtained in the previous section, the optimal RIS configuration is selected as

$$k^* = \arg \max_k |\hat{c}^{(k)}|^2, \quad (20)$$

Since the received SNR is proportional to the equivalent channel power $|c^{(k)}|^2$, maximizing $|\hat{c}^{(k)}|^2$ approximately maximizes the received SNR. The corresponding RIS matrix is therefore selected as

$$\Phi^* = \Phi^{(k^*)}. \quad (21)$$

This selection avoids iterative phase-shift optimization and reduces the need for full cascaded channel acquisition, thereby significantly lowering computational complexity and control overhead. In particular, the computational complexity is reduced from iterative RIS optimization (e.g., $\mathcal{O}(IN)$, where I and N denote the number of iterations and RIS elements, respectively) to a codebook-based search of $\mathcal{O}(K)$, independent of iterative convergence procedures and explicit CSI reconstruction.

VI. SIMULATION RESULTS AND DISCUSSION

The proposed RIS-assisted MISO-LoRa system is evaluated through MATLAB simulations in an indoor NLoS IIoT scenario. The RIS is placed 10 m from the device and 20 m from the gateway, while the direct link is neglected due to blockage. Both links follow quasi-static Rayleigh fading with path-loss exponent $\epsilon = 3$ and log-normal shadowing with 4 dB standard deviation, representative of indoor industrial LoRa environments. Channel estimation is performed using the LMMSE estimator, while RIS configuration selection is performed by evaluating a predefined RIS codebook

and selecting the configuration that maximizes the estimated equivalent channel gain, as described in Section V. The BER performance is evaluated via Monte Carlo simulations under fading, shadowing, and AWGN conditions over 1000 channel realizations. For brevity, results are presented for $SF = 8$, which corresponds to a representative mid-range LoRa configuration, as similar performance trends are observed across other spreading factors. System parameters are summarized in Table I. The adopted codebook size $K=16$ was selected to balance performance and training overhead. The SNR is defined as E_s/N_0 , where E_s denotes the average received symbol energy. “Fig. 3” illustrates the BER performance under differ-

TABLE I: Simulation parameters

Spreading Factor (SF)	8
Bandwidth (B_w)	125 kHz
Number of Transmit Antennas (P)	4 or 8
Number of RIS Elements (N)	{16, 32}
Codebook size (K)	16
P_t	14 dBm

ent channel and system configurations. As expected, Rayleigh fading degrades performance compared with the AWGN reference due to multipath effects and channel variability. The MISO-LoRa configuration provides diversity gains through multiple transmit antennas, leading to improved performance over the single-antenna case. To ensure a fair comparison, three baselines are considered: no RIS, random discrete phase shifts drawn from the same set as the proposed codebook, and a gradient-based RIS optimization method adapted from SISO RIS-LoRa systems [13]. The results show that the proposed RIS-assisted MISO-LoRa framework, combining LMMSE-based equivalent channel estimation with a low-complexity codebook-based RIS selection strategy, achieves consistent BER improvements over all baselines under realistic channel estimation conditions. These gains highlight the effectiveness of joint transmit diversity and RIS-assisted propagation in enhancing reliability under low-SNR industrial IoT scenarios.

At a target BER of 10^{-4} , the proposed system with $N = 16$ RIS elements achieves an SNR gain of approximately 8 dB over conventional LoRa in an AWGN channel, demonstrating the effectiveness of RIS-assisted signal enhancement in improving link reliability. In addition, it provides an SNR gain of approximately 3 dB compared to random phase shifts at the same BER target, highlighting the benefit of the proposed RIS phase configuration strategy. Increasing the number of RIS elements to $N = 32$ further improves performance, providing an additional SNR gain of approximately 3 dB at the same BER target. This gain highlights the scalability of the proposed RIS configuration strategy and the beneficial impact of increasing the number of reflecting elements on coherent signal combining.

Furthermore, increasing the number of transmit antennas P improves system performance by enhancing spatial diversity and strengthening the received signal power, particularly when combined with RIS-assisted transmission. Although a higher

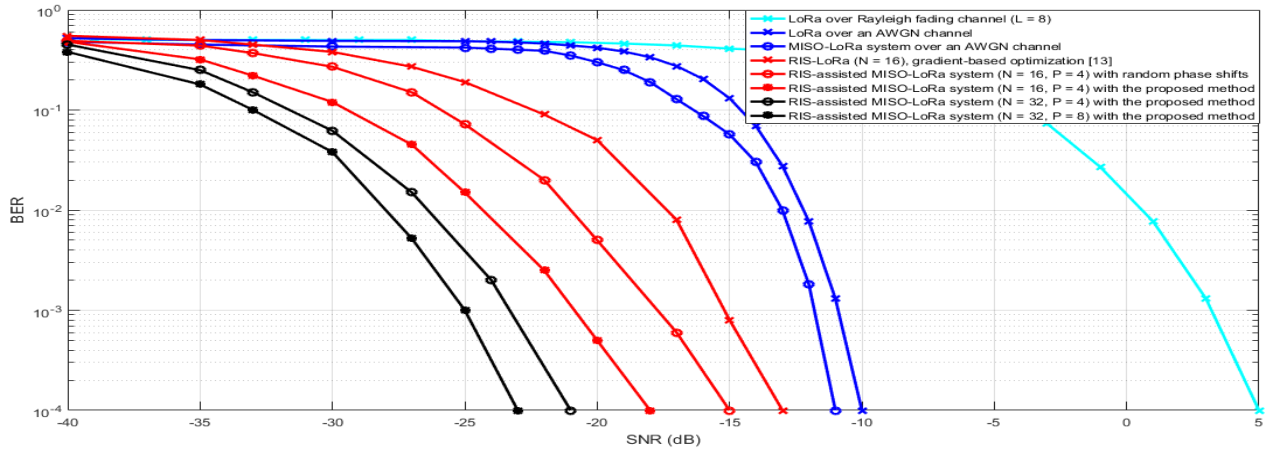


Fig. 3: BER performance of the proposed RIS- MISO LoRa .

P increases hardware complexity, it offers a favorable trade-off between performance improvement and implementation cost in resource-constrained IoT systems operating under strict energy limitations.

VII. CONCLUSION AND FUTURE WORKS

This paper proposed a RIS-assisted MISO-LoRa framework for reliable communications in harsh indoor industrial NLoS IIoT environments. By jointly exploiting transmit spatial diversity and RIS-enabled propagation control, the proposed approach enhances the received signal quality and improves BER performance compared with conventional LoRa and benchmark RIS-assisted schemes. To maintain low complexity, a scalar LMMSE-based channel estimation method and a codebook-based RIS phase selection strategy were adopted. Simulation results under realistic industrial propagation conditions demonstrated consistent performance gains, confirming the effectiveness and practical suitability of the proposed framework for future industrial IoT communications.

Future work will extend the proposed framework to outdoor and hybrid propagation environments. Joint optimization of transmit precoding and RIS phase configurations will be investigated to further enhance system performance under practical deployment constraints. In addition, the impact of imperfect CSI and multi-user communications will be studied to evaluate the robustness, scalability, and practical applicability of the proposed RIS-assisted MISO-LoRa architecture.

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