SHINE: Symbol-based Heuristic Iterative NB-LDPC Coded MIMO BP Detection and Decoding

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***Abstract*—In this letter, we propose SHINE, a Symbol-based Heuristic Iterative NB-LDPC codEd MIMO BP detection and decoding scheme. More specifically, we develop an NB-LDPC coded iterative detection and decoding (IDD) receiver equiped with a fine-tailored LLR interface between the real-domain detection and the Galois-field decoding. To further reduce the complexity of the IDD receiver, we propose a *Joint Symbol Pruning Optimization* (*JSPO*) framework, leveraging metaheuristic learning to jointly optimize the symbol search space in both detection and decoding. Numerical results demonstrate that compared with its basic version, SHINE succeeds in achieving up to 37.32% and 58.31% complexity reduction for the detection and the decoding w/o performance degradation. Numerical results also demonstrate the performance merits of the proposed SHINE compared with other NB-LDPC coded IDD counterparts.**

***Index Terms*—iterative detection and decoding (IDD), belief propagation (BP), NB-LDPC codes, multiple-input multiple-output (MIMO), metaheuristic learning.**

I. Introduction

RELIABILITY requirements in modern wireless communications have promoted extensive research on iterative detection and decoding (IDD) receivers. These receivers outperform conventional separate detection and decoding (SDD) methods by leveraging soft information exchange [1]. Operating in high-order Galois fields, non-binary low-density parity-check (NB-LDPC) codes offer superior error-correction capability, cycle-breaking properties, and natural compatibility with higher-order modulation over their binary counterparts [2]. However, implementing NB-LDPC coded IDD receivers remains challenging due to their prohibitively high complexity in both iterative processing and high-dimensional operations.

For detection, belief propagation (BP) detection offers an effective balance between performance and complexity in large-scale MIMO systems. The transition to real-domain processing [3] reduces computational complexity while maintaining performance compared to complex-domain approaches [4]. For decoding, the extended min-sum (EMS) decoder [5] has gained recognition for its efficient decoding performance with low complexity. Notably, both algorithms share inherent BP-based message-passing characteristics that can be exploited.

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BP detectors are often integrated with binary decoders for coded MIMO systems [6]. Recent approaches have leveraged machine learning techniques to maximize receiver performance [7]. While successful in binary domains, NB-LDPC decoders pose unique interface challenges due to the domain mismatch between detection outputs and Galois field operations. Previous attempts [8] suffer from exhaustive symbol enumeration and rely on complex-domain symbol processing, making them impractical for large-scale MIMO. Recent improvement [9], though noteworthy, remains limited to small-scale MIMO and SDD approaches. Motivated by the superior error-correction capability of NB-LDPC codes and the advantages of iterative processing, while alleviating their heavy computational load, we propose SHINE, a Symbol-based Heuristic Iterative NB-LDPC codEd MIMO BP detection and decoding scheme. The main contributions are listed as follows:

- **Proposing SHINE receiver**: The symbol-based heuristic iterative receiver for NB-LDPC coded MIMO systems is proposed. To the authors' best knowledge, this is the first complexity-affordable IDD receiver based on the BP algorithm for NB-LDPC coded massive MIMO systems.
- **Designing LLR interface**: A fine-tailored symbol-level LLR interface is designed to efficiently preserve reliability information while enabling rapid convergence. Benefiting from this interface, the proposed SHINE delivers up to $0.6\,\text{dB}$ performance gains over other NB-LDPC coded IDD counterparts at FER of 10^{-3} in 32×8 MIMO.
- **Developing *JSPO* framework**: A joint symbol pruning optimization framework is developed, leveraging metaheuristic learning to optimize the symbol search space. Numerical results demonstrate that SHINE with the *JSPO* framework achieves substantial complexity reduction for detection and decoding w/o performance penalization.

II. Preliminaries

A. System Model

Assuming an uplink MIMO system with N_t transmit antennas and N_r receive antennas, the received signal in real-domain $\mathbf{y} \in \mathbb{R}^{2N_r}$ can be illustrated as

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

where $\mathbf{H} \in \mathbb{R}^{2N_r \times 2N_t}$ represents the real-domain channel matrix, with each element following *Gaussian* distribution with zero mean and unitary variance. The transmitted symbol vector $\mathbf{x} \in \mathbb{R}^{2N_t}$ consists of symbols selected from a real-valued constellation $\sqrt{\mathcal{A}}$, derived from the original complex one with $|\mathcal{A}| = 2^Q$, where Q denotes the modulation order. The noise vector $\mathbf{n} \in \mathbb{R}^{2N_r}$ follows $n_i \sim \mathcal{N}(0, \sigma_n^2)$.

B. Real-domain BP Detection

The BP detection achieves competitive performance in large-scale MIMO systems by message passing on a factor graph with factor nodes (FNs) and symbol nodes (SNs) [3]. Real-domain BP decomposes the complex constellation into its real and imaginary components, which can potentially reduce the computational complexity, especially for higher-order modulations. The message sent from the i-th FN to the j-th SN is computed as

$$\beta_{i,j}(k) = \frac{(\zeta_{i,j} - h_{i,j}\mu_1)^2}{2\vartheta_{i,j}^2} - \frac{(\zeta_{i,j} - h_{i,j}\mu_k)^2}{2\vartheta_{i,j}^2}, \quad (2)$$

where μ_k denotes the k-th constellation point in $\sqrt{\mathcal{A}}$, and $\zeta_{i,j} = y_i - \sum_{l=1,l\neq j}^{2N_t} h_{i,l}\bar{s}_l$ represents the interference-cancelled received signal. The multiple-user interference (MUI) is approximated by *Gaussian* distribution $\mathcal{N}(\xi_{i,j}, \vartheta_{i,j}^2)$, where the mean and variance are computed as: $\xi_{i,j} = \sum_{l=1,l\neq j}^{2N_t} h_{i,l}\hat{\mathbb{E}}[s_l]$, and $\vartheta_{i,j}^2 = \sum_{l=1,l\neq j}^{2N_t} h_{i,l}^2 \hat{\mathbb{V}}[s_l] + \sigma^2$. The *a prior* probability $\mathcal{P}(s_j = \mu_k)$ is updated following:

$$\mathcal{P}_{j,i}^{(t)}(s_j = \mu_k) \approx \mathbb{N}\left[\exp\left(\alpha_{j,i}^{(t)}(k) - \max_{m\in\mathcal{U}} \alpha_{j,i}^{(t)}(m)\right)\right], \quad (3)$$

where $\mathbb{N}[x]$ denotes the normalization operator, $\mathcal{U}$ denotes the set of all possible symbol values in the constellation, and $\alpha_{j,i}(k)$ represents the message from the j-th SN to the i-th FN: $\alpha_{j,i}(k) = \sum_{t=1,t\neq i}^{2N_r} \beta_{t,j}(k)$. Once the maximum iteration number is reached, the BP detector proceeds to calculate the output of the j-th symbol: $\gamma_j(k) = \sum_{t=1}^{2N_r} \beta_{t,j}(k)$.

C. EMS Decoding

The EMS decoding algorithm has garnered widespread recognition for its adept balance between computational complexity and decoding efficiency for NB-LDPC codes [5]. Messages are conveyed in the form of LLRs between variable nodes (VNs) and check nodes (CNs). Permutation nodes serve as intermediaries for message relay over $GF(q)$. Denote $\{V_{pv}\}_{v=1..d_v}$ as the messages entering a VN and $\{U_{vp}\}_{v=1..d_v}$ as the output of this VN. The top n_m elements from the descendingly sorted q-dimensional LLR vector are assigned to U_{vp}. A reduced subset is introduced:

$$\mathrm{Conf}_{i_{d_c}(x)}(\psi_m, \psi_c) = \Big\{\boldsymbol{\alpha}_\mathbf{k} \in \mathrm{Conf}(\psi_m, \psi_c) : h_{d_c}(x) i_{d_c}(x) + \sum_{c=1}^{d_c-1} \alpha_c^{(k_c)}(x) = 0\Big\}, \quad (4)$$

where ψ_m and ψ_c retain only the most probable, meaningful configurations to reduce complexity. Then the CNs with the $d_c - 1$ incoming U_{pc} are updated following: $V_{d_c p} = \max_{\boldsymbol{\alpha}_\mathbf{k} \in \mathcal{S}_{i_{d_c}(x)}} \{L(\boldsymbol{\alpha}_\mathbf{k})\}$, where $\mathcal{S}_{i_{d_c}(x)} = \mathrm{Conf}_{i_{d_c}(x)}(q, 1) \cup \mathrm{Conf}_{i_{d_c}(x)}(\psi_m, \psi_c)$. Upon receiving $\{V_{pv}\}_{v=1..d_v}$ from CNs, each VN is updated as: $U_{tp} = L + \sum_{v=1,v\neq t}^{d_v} V_{pv}, t = 1, \ldots, d_v$, where L is the message transmitted by the initial channel.

III. Proposed SHINE Receiver

In this section, we present SHINE, an IDD receiver for NB-LDPC coded MIMO systems, featuring an optimized Real-to-Galois LLR interface and a metaheuristic-based *JSPO* framework for efficient computation with negligible performance degradation.

A. Optimized Real-to-Galois Domain IDD Architecture

In designing IDD receivers for NB-LDPC coded MIMO systems, the primary challenge lies in the domain mismatch between real-valued detection outputs and Galois field decoding operations, which demands an efficient symbol-level LLR interface. This interface must simultaneously preserve reliability information to maximize error-correction performance while ensuring rapid convergence to minimize computational complexity—a balance particularly critical in high-order modulation and large-scale MIMO systems. To systematically address this, we develop an cross-domain receiver architecture that bridges the detection-decoding gap through carefully designed message exchange mechanisms, as illustrated in Fig. 1.

Assuming the statistical independence of real and imaginary parts and the additive contribution of each bit to the metric in the exponential, we express the symbol reliability through bit-wise *a posteriori* probability (APP) LLR for the k-th bit of the i-th symbol as:

$$\begin{aligned} L_{A,i,k} &\triangleq \ln \frac{P(x_{i,k} = 0|\mathbf{y})}{P(x_{i,k} = 1|\mathbf{y})} \\ &= \ln \frac{\sum_{\mathbf{x}^\Re \in \mathcal{X}_{k,x_{i,k}=0}^\Re} \exp\left(-\frac{1}{2\sigma^2}\|\mathbf{y}^\Re - \mathbf{H}^\Re \mathbf{x}^\Re\|^2\right) P(\mathbf{x}^\Re)}{\sum_{\mathbf{x}^\Re \in \mathcal{X}_{k,x_{i,k}=1}^\Re} \exp\left(-\frac{1}{2\sigma^2}\|\mathbf{y}^\Re - \mathbf{H}^\Re \mathbf{x}^\Re\|^2\right) P(\mathbf{x}^\Re)} \\ &\quad + \ln \frac{\sum_{\mathbf{x}^\Im \in \mathcal{X}_{k,x_{i,k}=0}^\Im} \exp\left(-\frac{1}{2\sigma^2}\|\mathbf{y}^\Im - \mathbf{H}^\Im \mathbf{x}^\Im\|^2\right) P(\mathbf{x}^\Im)}{\sum_{\mathbf{x}^\Im \in \mathcal{X}_{k,x_{i,k}=1}^\Im} \exp\left(-\frac{1}{2\sigma^2}\|\mathbf{y}^\Im - \mathbf{H}^\Im \mathbf{x}^\Im\|^2\right) P(\mathbf{x}^\Im)}, \end{aligned} \quad (5)$$

where $(\cdot)^\Re$ and $(\cdot)^\Im$ denote the real and imaginary parts, respectively, $\mathcal{X}_{k,x_{i,k}}^\Re$, $\mathcal{X}_{k,x_{i,k}}^\Im$ are the sets of real and imaginary symbol vectors. Eq. (5) reveals that the total LLR $L_{A,i,k}$ can be decomposed into real and imaginary components:

$$\begin{aligned} L_{A,i,k} &= \ln \frac{P(x_{i,k}^\Re = 0|\mathbf{y}^\Re)}{P(x_{i,k}^\Re = 1|\mathbf{y}^\Re)} + \ln \frac{P(x_{i,k}^\Im = 0|\mathbf{y}^\Im)}{P(x_{i,k}^\Im = 1|\mathbf{y}^\Im)} \\ &= L_{A,i,k}^\Re + L_{A,i,k}^\Im. \end{aligned} \quad (6)$$

The decomposition enables efficient computation of $L_{A,i,k}$ using real-domain outputs while preserving essential probabilistic information for decoding.

Next, to map the aggregated LLRs to corresponding $GF(q)$ symbols required by the NB-LDPC decoder, a bijective symbol mapping function $\Psi_{\mathbb{R}\to\mathrm{GF}(q)}$ is introduced, which translates the real-valued LLR vector $\mathbf{L}_i = [L_{i,1}, \ldots, L_{i,K}]^\top$, where K is the number of bits per symbol, into a symbol in $GF(q)$:

$$s_i = \Psi_{\mathrm{LLR}\to\mathrm{GF}(q)}(\mathbf{L}_i) = \arg\max_{s\in\mathrm{GF}(q)} \sum_{k=1}^{K} (1 - 2b_{s,k}) L_{i,k}, \quad (7)$$

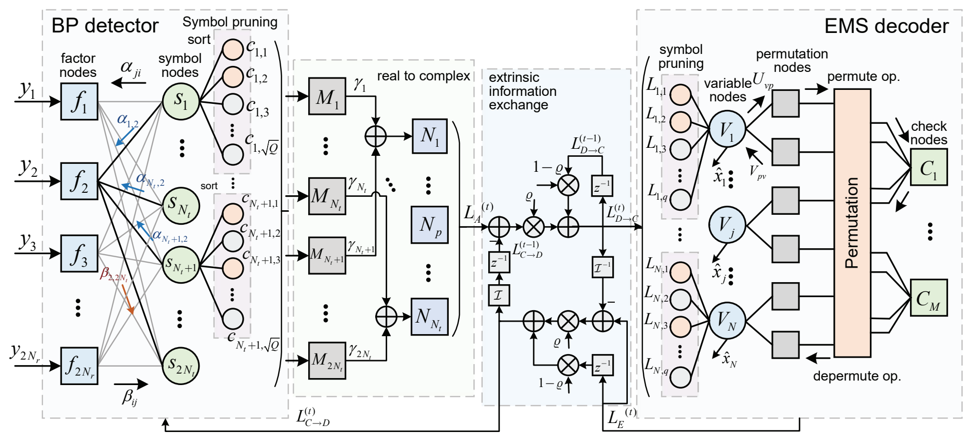


Fig. 1. Architecture of the proposed SHINE receiver incorporating real-domain BP detection, EMS decoding, and symbol-based pruning optimization.

where $b_{s,k}$ is the k-th bit of the binary representation of symbol s. This maximization selects the $GF(q)$ symbol that is most likely given the LLRs.

To manage extrinsic information exchange and ensure convergence in the IDD process, we introduce a damped update mechanism with interleaving:

$$\begin{cases} L_{D\to C}^{(t)} = \varrho\left(L_A^{(t)} - \mathcal{I}\left\{L_{C\to D}^{(t-1)}\right\}\right) + (1-\varrho)L_{D\to C}^{(t-1)}, \\ L_{C\to D}^{(t)} = \varrho\left(L_E^{(t)} - \mathcal{I}^{-1}\left\{L_{D\to C}^{(t)}\right\}\right) + (1-\varrho)L_{C\to D}^{(t-1)}. \end{cases} \quad (8)$$

Here, $L_{D\to C}^{(t)}$ and $L_{C\to D}^{(t)}$ are extrinsic LLRs passed between detector and decoder, $L_A^{(t)}$ and $L_E^{(t)}$ are *a posteriori* and extrinsic LLRs from detector and decoder respectively, $\mathcal{I}\{\cdot\}$ and $\mathcal{I}^{-1}\{\cdot\}$ are interleaving functions to decorrelate information, and $\varrho \in [0,1]$ is a damping factor to mitigate potential oscillations and accelerate convergence. This symbol-level approach combined with the damped update mechanism ensures both error-correction performance and convergence efficiency in NB-LDPC coded MIMO systems.

B. Joint Heuristic Symbol Pruning for Complexity Reduction

Despite the superior performance of NB-LDPC coded IDD receivers, the high-dimensional symbol space in $GF(q)$ introduces significant computational complexity. While the adoption of real-domain symbol processing in detection partially mitigates this issue, the overall IDD receiver remains computationally intensive. Notably, both BP detection and EMS decoding operate in the symbol domain, where the symbol probability distributions exhibit sparsity. This sparsity can be exploited to jointly reduce complexity by intelligently pruning unlikely symbol candidates.

In this work, we propose a *Joint Symbol Pruning Optimization* (*JSPO*) framework that jointly optimizes symbol pruning in both BP detection and EMS decoding. By adapting the symbol search space based on probabilistic significance, the *JSPO* effectively reduces computational complexity while maintaining error performance.

1) Symbol Pruning in BP Detection: In BP detection, messages $\alpha_{j,i}(k)$ are computed for all possible symbols $\mu_k \in \sqrt{\mathcal{A}}$. However, many of these symbols contribute negligibly due to their low likelihood. To reduce complexity, we introduce an adaptive pruning threshold n_d to dynamically control the symbol search space. Define the symbol index set for the j-th SN as $\mathcal{K}_j = 1, 2, \ldots, |\sqrt{\mathcal{A}}|$. We formulate the pruned symbol subset $\mathcal{K}_j^{(n_d)}$ through a probabilistic ranking function $\mathcal{R}(\cdot)$:

$$\mathcal{K}_j^{(n_d)} = \mathcal{R}\left(\alpha_{j,i}(k)_{k\in\mathcal{K}_j}, n_d\right), \quad (9)$$

where $\mathcal{R}(\cdot)$ selects the n_d symbols with the highest probabilistic significance. The pruned *a priori* probability is then approximated as

$$\mathcal{P}_{j,i}^{(t)}\left(s_j = \mu_k\right) \approx \begin{cases} \mathbb{N}\left[\exp\left(\alpha_{j,i}^{(t)}(k) - C_j\right)\right], & k \in \mathcal{K}_j^{(n_d)} \\ 0, & \text{otherwise} \end{cases} \quad (10)$$

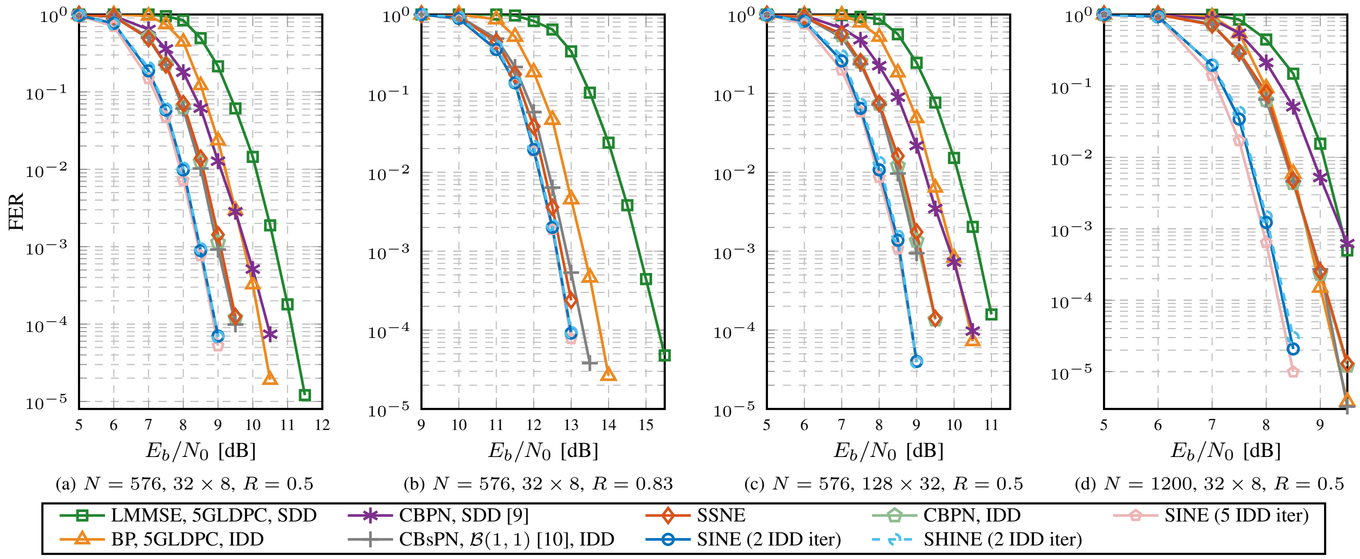
where $C_j = \max_{m\in\mathcal{K}_j^{(n_d)}} \alpha_{j,i}^{(t)}(m)$ ensures numerical stability. By limiting the computation of $\beta_{i,j}(k)$ and subsequent messages to symbols in $\mathcal{K}_j^{(n_d)}$, we significantly reduce the computational load while retaining the most probable symbol candidates.

2) Symbol Pruning in EMS Decoding: In EMS decoding, the computational complexity is also substantial due to processing all q possible symbols at each VN and CN. We introduce a pruning threshold n_c, truncating the input LLR vector $\gamma_j(k)$ to retain only the top n_c symbols with the highest reliabilities for each VN. Let $\Gamma_j = \{\gamma_j(k)\}_{k=1}^q$ be the set of LLRs for the j-th VN. $\arg\text{top}$ returns the indices with the n_c largest values. The pruned set $\Gamma_j^{(n_c)}$ is defined as

$$\Gamma_j^{(n_c)} = \arg\text{top}_{k\in\{1,2,\ldots,q\}}\left\{\gamma_j(k)\right\}_{n_c}. \quad (11)$$

Only symbols within $\Gamma_j^{(n_c)}$ are considered in the VN and CN updates, reducing complexity while focusing on the most probable symbol candidates.

3) Collaborative Optimization Framework: Our proposed *JSPO*, a customized evolutionary multi-objective optimization approach, leverages metaheuristic learning to efficiently navigate the discrete, non-linear optimization of symbol pruning thresholds. It employs evolutionary operations—selection, crossover, and mutation—to explore the solution space despite the coupled effects between n_d, n_c, and stringent FER



(a) $N = 576$, 32×8, $R = 0.5$ (b) $N = 576$, 32×8, $R = 0.83$ (c) $N = 576$, 128×32, $R = 0.5$ (d) $N = 1200$, 32×8, $R = 0.5$

Fig. 2. FER performance comparison of various code lengths, code rates and MIMO scenarios employing 64-QAM modulation, with $GF(64)$.

constraints. Alternative approaches like simulated annealing and particle swarm optimization prove suboptimal for this problem due to slow convergence and inefficiency with discrete variables. Tree search heuristics remain computationally prohibitive given the combinatorial search space.

The optimization problem is formulated as:

$$\begin{aligned} \min_{n_d, n_c} \quad & \mathcal{J}(n_d, n_c) = w \cdot \mathbb{E}[n_d] + (1-w) \cdot \mathbb{E}[n_c], \\ \text{subject to} \quad & \text{FER}_\chi(n_d, n_c) \leq \text{FER}_\iota + \delta_{\text{FER}}, \\ & n_d^{\min} \leq n_d \leq n_d^{\max}, \quad n_c^{\min} \leq n_c \leq n_c^{\max}, \end{aligned} \tag{12}$$

where $\mathbb{E}[n_d]$ and $\mathbb{E}[n_c]$ are the expected symbol numbers after pruning in detection and decoding, $w \in [0,1]$ is the weight balancing their contributions, FER_χ and FER_ι are the frame error rates with and without pruning, respectively, and δ_{FER} is a small tolerance (e.g., 1×10^{-6}). The parameters in Table I are carefully chosen empirically, with ϱ and n_c specifically optimized via Monte Carlo simulations to balance exploration and convergence. Our implementation employs SMS-EMOA with SBX crossover and PM mutation operators, preserving reproducibility through deterministic random seeding.

TABLE I
PARAMETERS OF THE *JSPO* FRAMEWORK

Parameter	**Value**	**Parameter**	**Value**
FER Tolerance δ_{FER}	10^{-6}	Damping Factor ϱ	0.7
Pruning Range for n_d [3]	$[1, 8]$	Pruning Range for n_c [5]	$[1, 40]$
Population Size N_{p}	100	Maximum Epoch $I_{\max}$	2000
Mutation Prob $\mathbb{P}_\Xi$	0.9	Crossover Prob $\mathbb{P}_\Upsilon$	1.0
SBX Dist. Index Θ	15	PM Dist. Index Φ	20

IV. Numerical Results

We evaluate the error-correction performance and complexity of SHINE's across various code lengths, rates, and MIMO configurations with 64-QAM modulation. SSNE (SDD-based) and SINE (IDD-based) represent the versions of SHINE without heuristic learning. Comparisons include an adapted version of the complex-domain symbol-based BP detection and decoding interface (CBPN) from [8], [9], replacing its high-complexity BP detection algorithm with our complex-domain BP to enable large-scale MIMO implementation. The belief-selective propagation detector from [10] serves as an additional benchmark (CBsPN). Binary LDPC codes following 5G NR standard ensure fair comparison. The weighting factor w is set to the pre-learning detection-to-total complexity ratio for balanced assessment. The *JSPO* framework is trained at SNR points corresponding to FER of 10^{-2}. Initial simulations employ $n_d^{\max} = 8$ and $n_c^{\max} = 40$, with 3 internal BP detection iterations and 4 EMS decoding iterations per IDD iteration.

A. Performance Analysis

Fig. 2 shows SHINE's FER performance versus existing receivers across diverse configurations, with case (d) following BeiDou satellite standard [11]. Simulation results demonstrate that two detection-decoding iterations suffice to achieve optimal performance of the proposed IDD receiver, with additional iterations yielding negligible improvements, confirming the rapid convergence capability. Building upon this observation, all IDD benchmark receivers are configured with two iterations for fair comparison. CBPN's performance in high-rate scenarios is omitted due to severe error floor issues stemming from its suboptimal handling of dense parity-check matrices.

For SDD, SSNE outperforms conventional approaches. Compared to 5G LDPC-coded LMMSE, SSNE yields approximately 1.5 dB gain at FER=10^{-3} for moderate configurations, with a 1.0 dB advantage for longer codes. For IDD, SHINE shows improvements over binary LDPC counterparts. SHINE achieves around 1.0 dB gain over 5G LDPC-coded BP IDD across different configurations, including the 128×32 MIMO system where the performance advantage remains consistent. This performance gain stems from the inherent advantage of NB-LDPC codes, their natural synergy with higher-order modulations, and our efficient IDD architecture. Compared to CBPN IDD, SHINE demonstrates superior performance with 0.6-0.8 dB gain across various configurations, benefiting

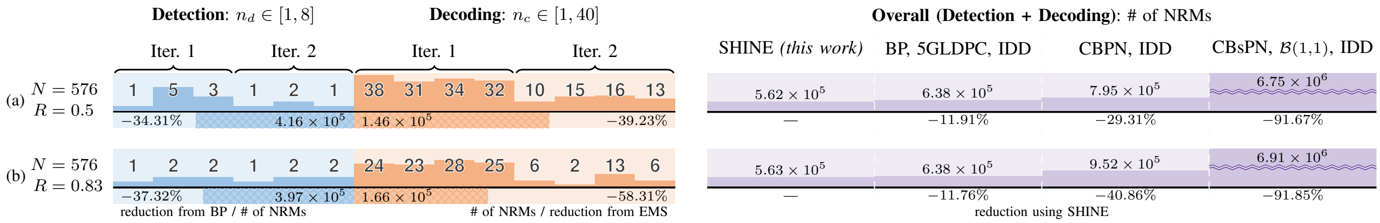


Fig. 3. Complexity comparison for different MIMO-NBLDPC configurations corresponding to Fig. 2.

from real-domain processing and our optimized LLR interface. Compared to CBsPN IDD, SHINE also exhibits consistent performance advantages, stemming from our improved symbol selection strategy that maximizes information propagation while maintaining controlled complexity. Furthermore, SHINE achieves nearly identical performance to SINE while substantially reducing complexity by adaptively retaining significant symbol candidates based on reliability metrics.

B. Complexity Reduction Analysis

The complexity analysis of SHINE in BP detection encompasses LMMSE initialization, $\beta_{i,j}(k)$ calculation, $\alpha_{j,i}(k)$, $\mathcal{P}_{j,i}$, $\gamma_j(k)$ update, and additionally introduces a pruning step. For each of the three internal iterations within one detection phase, SHINE requires $\mathcal{O}(4N_rN_t|\sqrt{\mathcal{A}}| + 2N_rN_tn_d) + \mathcal{O}\left(N_t^3\right)$ multiplications, $\mathcal{O}(4N_rN_t|\sqrt{\mathcal{A}}| + 6N_rN_tn_d) + \mathcal{O}\left(N_t^3\right)$ additions, $\mathcal{O}(2N_rN_tn_d)$ exponentiations, and $\mathcal{O}(2N_rN_t|\sqrt{\mathcal{A}}|\log n_d)$ comparisons. In contrast, the real-domain BP detection requires $\mathcal{O}(6N_rN_t|\sqrt{\mathcal{A}}|) + \mathcal{O}\left(N_t^3\right)$ multiplications, $\mathcal{O}(10N_rN_t|\sqrt{\mathcal{A}}|) + \mathcal{O}\left(N_t^3\right)$ additions, and $\mathcal{O}(2N_rN_t|\sqrt{\mathcal{A}}|)$ exponentiation. SHINE achieves substantial complexity reduction, particularly in exponentiations and post-pruning operations, where the complexity is reduced from $\mathcal{O}(N_rN_t|\sqrt{\mathcal{A}}|)$ to $\mathcal{O}(N_rN_tn_d)$. For the decoder part, following the complexity analysis in [5], we evaluate the EMS algorithm's complexity in: variable node processing $\mathcal{O}(Nd_vq)$, check node processing $\mathcal{O}(Md_cn_cq)$, and configuration set generation $\mathcal{O}(Md_c[q + (n_c - 1)\log q])$, which are dominated by addition operations. Since the computational overhead of heuristic learning can be performed offline, and only addition-level operations are introduced in online joint detection and decoding, SHINE achieves significant complexity reduction compared to SINE with minimal implementation overhead.

To provide a quantitative complexity comparison, we utilize real-valued multiplications (NRMs) as the complexity metric. Each complex multiplication involves 4 NRMs and 2 real additions, while each complex addition requires 2 real additions. Following quantization, one exponential and real addition equal to m and $1/k$ NRMs respectively, where $m = 8$ and $k = 14$ represent the bit width of addition and exponentiation. As shown in Fig. 3, SHINE achieves substantial complexity reduction through its probability-guided symbol pruning, resulting in enhanced energy efficiency for resource-constrained systems. The *JSPO* framework strategically prunes the detection and decoding search spaces based on reliability metrics, reducing computational burden while preserving performance integrity. SHINE's rapid convergence in just two iterations further enhances its efficiency advantage over conventional IDD approaches. Compared to other IDD receivers, SHINE delivers complexity reductions (11.8-91%) while maintaining superior performance. These optimizations bring SHINE's computational requirements close to conventional SDD approaches (8.5%-21.5% overhead) while delivering the performance benefits of iterative processing. For increasing antenna scales and modulation orders, SHINE's complexity reduction remains effective, while higher-order modulations enable even more gains due to the natural isomorphism between constellation points and GF elements.

V. Conclusion

We propose SHINE, a symbol-based heuristic iterative receiver for NB-LDPC coded MIMO systems. The optimized Real-to-Galois LLR interface enables efficient probabilistic information exchange. By designing the *JSPO* framework through reliability-guided optimization, SHINE shows significant complexity reduction without performance degradation.

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