

## Intelligent DRL-assisted decoding of error-correcting codes for 5G/6G telecommunication channels

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This paper presents an intelligent decoding methodology for low-density parity-check (LDPC) and Polar codes (P-C) based on deep reinforcement learning (DRL+Soft) for modern 5G and emerging 6G communication systems. The proposed decoder adapts its decoding strategy in real-time, optimizing bit error rate (BER) performance under varying channel conditions. Evaluation is formulated through performance metrics including BER convergence, reward dynamics, computational complexity (FLOPs), and inference latency. Simulation results show that the DRL+Soft decoder achieves up to a 2.5-fold reduction in computational cost and decreases inference time from 4.8 ms (BP) to 1.6 ms per data block, while maintaining superior BER compared to classical belief propagation (BP) and cyclic redundancy check-aided successive cancellation list (CA-SCL) decoders. The decoder exhibits improved robustness against unpredictable interference and channel impairments, making it suitable for dense device deployments and ultra-reliable low-latency communication (URLLC) scenarios. The methodology also supports reprogramming or retraining of DRL agents without hardware changes, ensuring long-term adaptability for evolving 6G networks. These results demonstrate both theoretical novelty and practical value, providing a scalable and energy-efficient solution for future wireless communication systems.

Keywords: deep reinforcement learning, LDPC codes, polar codes, 5G/6G communications, BER optimization

### 1 Introduction

The rapid evolution of telecommunication networks toward 5G and beyond has significantly increased the demands placed on physical layer technologies. Future 6G systems are expected to support unprecedented data rates, URLLC [1], and energy-efficient operation across diverse environments. At the core of these requirements lies error-correcting coding [2-5], where LDPC codes and P-C [6, 7] have become the de facto standards due to their capacity-approaching performance. Nevertheless, conventional decoding algorithms, such as BP for LDPC and SC [8] or its list variants for P-C, exhibit limitations under harsh conditions. In channels affected by multipath fading, nonlinear distortions, or dynamic interference, their iterative nature leads to high complexity, longer latency, and degraded reliability, especially at low signal-to-noise ratios (SNR) [9]. These limitations highlight the need for adaptive, intelligent decoding approaches, motivating the use of DRL-based decoders for next-generation wireless systems.

To address these challenges, the integration of artificial intelligence (AI) into the decoding process has emerged as a promising research direction. Unlike deterministic algorithms, AI-based models – ranging from

deep neural networks (DNNs) to graph neural networks (GNNs) – can learn complex decision functions directly from channel observations. For LDPC codes, the Tanner graph structure [4, 5] naturally aligns with GNN architectures, allowing the decoder to optimize message passing across factor nodes while reducing the required number of iterations. Similarly, neural enhancements of polar decoding [6] can adapt list-based strategies by exploiting statistical information from prior decoding attempts. Importantly, such approaches introduce adaptivity, enabling decoders to generalize across varying channel conditions without the need for explicit mathematical re-derivations.

Furthermore, reinforcement learning, and in particular DRL, provides an additional dimension by enabling the decoder to optimize its decision-making policy in dynamic channel environments. This paradigm transforms decoding into an adaptive process, where the system continuously improves its performance based on interaction with the environment. Beyond algorithmic efficiency, AI-driven decoding opens opportunities for energy-aware implementations in edge and Internet of Things (IoT) devices, where computational and power constraints are critical. As a result, AI-assisted decoding can bridge the gap between the stringent reliability and

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latency requirements of 5G/6G telecommunication [10] channels and the limitations of conventional methods, paving the way toward intelligent, cognitive receivers.

One promising approach to tackle these challenges is integrating AI into the decoding process. Unlike fixed, rule-based algorithms, AI models – including DNNs, GNNs, and RNN/LSTM architectures – can infer complex decision mappings directly from channel observations. In LDPC decoding, Tanner graph structures naturally complement GNN designs, enabling efficient message propagation across factor nodes and fewer iterations. Polar decoding benefits from neural-guided adaptations of list-based strategies, leveraging statistical insights from previous decoding attempts. Recurrent models, such as recurrent neural networks (RNNs) and long short-term memory (LSTM), extend capabilities to channels with memory, mitigating inter-symbol interference though requiring more intensive training. Building on these foundations, DRL reframes decoding as a sequential decision-making problem, where an agent adaptively adjusts bit manipulations, reweighting strategies, or stopping criteria based on reward feedback tied to decoding accuracy. Actor-critic and Q-learning approaches demonstrate strong adapt-ability under dynamic channels and unconventional code structures, though reward design and training complexity remain challenges. These AI-driven decoders highlight complementary strengths, motivating hybrid strategies that combine soft-decision reliability with DRL-based adaptivity to deliver robust, energy-efficient, and deployment-ready solutions for 5G and 6G systems [7].

Existing literature underscores both the promise and limitations of neural-aided decoding. Paper [11] focused on software-defined high-throughput LDPC and P-C decoders optimized for GPU acceleration, achieving impressive coded throughputs but leaving algorithmic adaptability unaddressed. Paper [12] introduced DL-assisted fast successive cancellation (DL-FSC) for P-C, partitioning the decoding process into learnable sub-blocks to improve throughput; however, the method remained confined to deterministic SC structures without strategic adaptability. A line of work on neural BP [13-15] addressed complexity reduction and robustness against short cycles in Tanner graphs. These studies demonstrated performance gains through pruning, quantization, or tensor-ring compression, but still inherit structural rigidity from message-passing formulations. Other contributions, such as [16] on structural neural BP and [17] on LSTM-based channel prediction, extend the scope of deep learning in communication but remain detached from adaptive decoding strategies. Finally, [18] highlighted AI's transformative role in network-level optimization for 5G/6G [19], yet without bridging it to symbol-level intelligent decoding.

In light of these achievements, the proposed hybrid DRL+Soft decoding platform closes an important gap, namely, it utilizes the statistical soft decision decoding framework to provide DRL-based adaptivity to dynamically changing channel and code conditions. Unlike prior methods that optimize either algorithmic efficiency (e.g., GPU acceleration, pruning, quantization) or structural modeling (e.g., GNN, NBP), our approach jointly ensures robustness, adaptability, and practical feasibility. This positions the DRL+Soft hybrid decoder as a promising candidate for next-generation intelligent communication systems, complementing and extending the achievements of the existing state of the art.

## 2 Deep reinforcement learning (DRL) for intelligent LDPC and polar decoders in 5G/6G networks

DRL has emerged as a powerful paradigm for training agents capable of making decisions in complex, dynamic environments. In the context of decoding error-correcting codes – specifically LDPC and P-C relevant to 5G and 6G systems – DRL enables the design of intelligent decoders that adaptively select optimal decoding strategies under varying channel conditions, noise levels, and interference patterns. The ability to continuously adjust decision-making provides a significant advantage over static decoding algorithms.

DRL combines two fundamental components:

- 1) Reinforcement Learning (RL) – which allows an agent to learn by interacting with the environment and receiving feedback in the form of rewards.
- 2) Deep Learning (DL) – which employs NN (commonly DNNs, CNNs, or LSTMs) to approximate value functions or policy functions, thereby enabling complex decision-making in high-dimensional spaces.

Given the introduction of DRL-specific terminology, it is crucial to establish a context-aware vocabulary suitable for decoding applications in 5G networks. Within this framework, the agent is viewed as a decoder that operates on log-likelihood ratios (LLRs) or intermediate outputs of the decoding process. The environment is associated with the noisy communication channel together with the transmitted codeword. The state comprises the current set of LLRs, tentative bit decisions, and path-related metrics. An action can involve selecting a bit assignment or adapting the de-coding depth. The reward expresses the outcome of decoding, for instance by indicating success or failure of a Cyclic Redundancy Check (CRC) [6], or by reflecting improvements in the Block Error Rate (BLER). The primary objective of the DRL agent is to maximize the expected cumulative reward, formulated mathematically as

$$\max_{\pi} E_{\pi} \left[ \sum_{t=0}^T \gamma^t r_t \right] \quad (1)$$

where  $\pi$  denotes the policy parameterized by the NN,  $r_t$  is the instantaneous reward,  $\gamma \in [0,1]$  is the discount factor, and  $T$  is the episode length (in this case, the number of decoding steps),  $E_{\pi}$  denotes expectation with respect to trajectories generated by policy  $\pi$ .

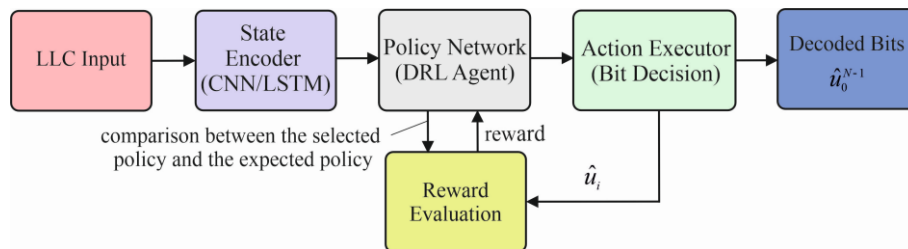
Possible DRL architectures include deep Q-networks (DQN) for discrete actions, Actor-critic or Deep Deterministic Policy Gradient (DDPG) for continuous strategies, and Policy Gradient methods for direct policy optimization.

For P-C, DRL can be applied to SC/SCL (Successive Cancellation List decoding) [19] decoding graphs, enabling adaptive path selection. For LDPC codes, the agent decides on bit corrections based on Tanner graph messages [4]. This approach allows decoders to transcend fixed rules (e.g., pure Min-Sum algorithm (MS) [4] or algorithms BP [5, 20]) and dynamically adapt to real-time channel conditions. Additionally, the DRL agent can account for channel memory, which is crucial for Rayleigh fading or Inter-Symbol Interference (ISI) in OFDM (Orthogonal Frequency-Division Multiplexing) systems [10, 21], particularly in 5G/6G URLLC and IoT applications [18, 22].

The use of a DRL-driven decoder offers several key benefits. First, it provides inherent adaptivity, allowing the decoder to dynamically adjust its behavior in response to changing channel conditions. Second, it minimizes the need for manual configuration, as the decoding parameters are learned automatically through the training process. Third, the framework can be integrated with RNN [23] or LSTM networks, which enables the decoder to account for channel memory and temporal correlations in the received signals. These features collectively open the possibility for improved Bit Error Rate (BER) and BLER performance under challenging transmission scenarios, which will be demonstrated and analyzed in the experimental results.

The DRL decoder architecture proposed in this work includes the following blocks (see Fig. 1): 1) LLR Input – receives LLR values from the demodulator; 2) State Encoder (CNN/LSTM) – compresses the current state into a feature representation; 3) Policy Network (DRL Agent) – decides on actions based on the encoded state; 4) Reward Evaluation – computes the reward associated with actions; 5) Action Executor (Bit Decision) – applies the selected action to the bit(s); 6) Decoded Bits Output – outputs the final decoded sequence.

Figure 1 illustrates the full DRL-based decoder block diagram.



**Fig. 1.** Block diagram of the synthesized decoder based on the DRL concept

LLR values flow from the demodulator to the state encoder which converts them into a compact state representation. The policy network generates actions, which the action executor executes to produce decoded bits, while the reward evaluation block calculates the success metrics (e.g., CRC check or BER improvement).

A crucial aspect of DRL is the reward evaluation mechanism. As illustrated in Fig. 1, the reward block receives the action taken by the agent and compares it against expected outcomes. The feedback (reward signal) propagates back to the policy network, updating the agent's policy via reinforcement learning updates. This backward propagation ensures the decoder adapts intelligently, refining its policy based on past performance. Notably, the reward block considers not only executed actions but also the intentions of the agent, i.e., the probability distribution over potential actions. This

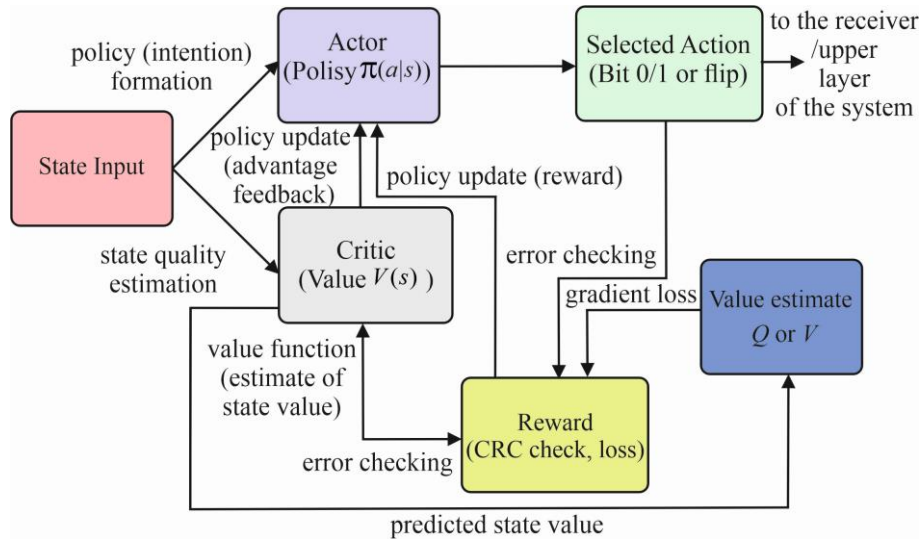
feature is critical for policy-based methods such as policy gradient and Actor-Critic approaches. For example, if the agent intended to choose action  $X$  but selected  $Y$ , the reward mechanism assesses alignment with overall goals, influencing future policy updates.

In an Actor-Critic DRL framework (see Fig. 2), the Actor generates a probability distribution over actions (agent intentions) based on the current state, reflecting potential bit selections or decoding strategies.

The Critic evaluates these actions, estimating the value function  $V(s_t)$  or action-value function  $Q(s_t, a_t)$  thus quantifying the quality of decisions. The reward block supplies feedback (0/1 or derived from a loss function) to guide learning. The Value Estimate provides intermediate assessment for updating Actor and Critic weights.

During LDPC and P-C decoding, LLRs from the code graph enter the state input. The Actor decides on the bit or message configuration, Critic evaluates the

decision, and the Reward signal, calculated from metrics like CRC, BLER, or decoding errors, adjusts the Actor accordingly.



**Fig. 2.** Actor-Critic framework illustrating the application of a DRL approach for an intelligent 5G/6G decoder

Mathematically, the state-value function is expressed as

$$V(s_t) = E_{\pi} \left[ \sum_{k=0}^{\infty} \gamma^k \cdot r_{t+k} | s_t \right] \quad (2)$$

where  $s_t$  represents the current decoding state (LLRs, previous decisions, etc.),  $r_t$  is the instantaneous reward,  $\gamma$  is the discount factor, and  $\pi$  denotes the policy. This function reflects the expected cumulative reward starting from state  $s_t$ , indicating decoder reliability under stochastic channel conditions.

The action-value function  $Q(s_t, a_t)$  is formulated as

$$Q(s_t, a_t) = E_{\pi} \left[ \sum_{k=0}^{\infty} \gamma^k \cdot r_{t+k} | s_t, a_t \right] \quad (3)$$

This evaluates the long-term quality of selecting a specific action  $a_t$  in state  $s_t$  (that is, the selection of a bit  $\hat{u}_t = 0$  or  $\hat{u}_t = 1$ ), guiding the decoder toward actions that minimize BLER and improve stability.

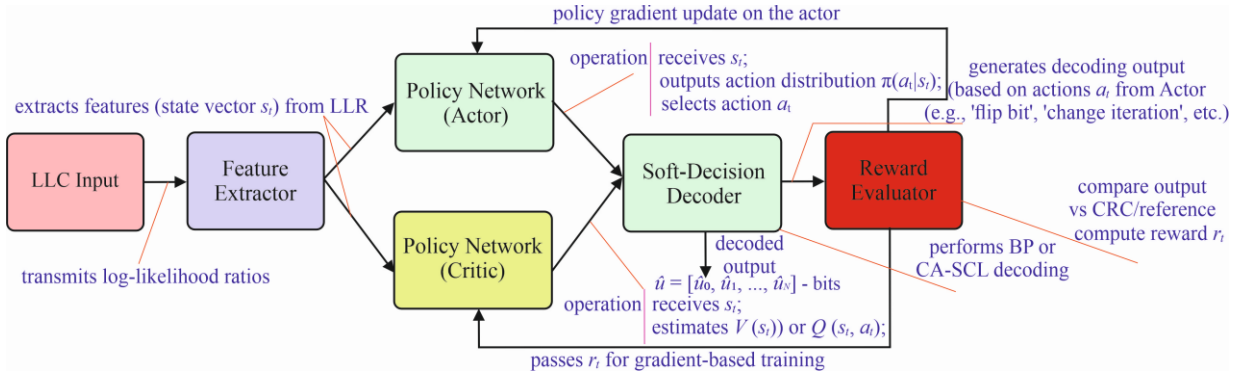
In the proposed scheme, the Reward block considers both executed actions and agent intentions, enabling policy-based RL methods to optimize over full probability distributions rather than individual actions.

This approach is compatible with hardware implementations such as Field-Programmable Gate Array (FPGA) [24], supporting real-time, energy-efficient decoding in 5G/6G and embedded AI applications [25].

### 3 Architecture of the proposed hybrid intelligent decoder (DRL + Soft-Decision) for 5G/6G

In this subsection, we introduce the architecture of a hybrid intelligent decoder for LDPC and P-C, which integrates the classical Soft-Decision approach with DRL, following the methodology described in the previous section. The main concept is to employ a DRL agent as a strategic decision-making module that adaptively adjusts to channel characteristics, code type, and interference level. This enables a significant enhancement in decoding performance, especially under highly dynamic conditions typical for 5G/6G systems.

Figure 3 illustrates the proposed hybrid architecture of the intelligent decoder (DRL Soft-Decision) for 5G/6G. The block diagram includes the following components: the LLR Input, which captures soft measurements from the channel; the Feature Extractor, which processes these inputs into a state vector  $s_t$ ; the Policy Network (Actor-Critic, DRL), where the Actor generates a probability distribution over potential



**Fig. 3.** Block diagram of the hybrid intelligent decoder architecture (DRL Soft-Decision) for 5G/6G decoder

actions (e.g., bit flips, bit fixation), and the Critic evaluates the value of a state or state-action pair in terms of parameters  $V(s_t)$  and  $Q(s_t, a_t)$ . Additionally, the decoder comprises a Soft-Decision Decoder (LDPC/Polar) – the classical decoding module using BP for LDPC and CA-SCL for P-C. The Reward Evaluator compares the decoder output against CRC checks or a known target to train the DRL agent.

The Reward  $R$  is computed from CRC checks or BLER reduction, the Critic estimates  $V(s)$  via temporal-difference updates, while  $Q(s, a)$  is calculated as

$$Q(s_t, a_t) = R_t + \gamma V(s_{t+1}).$$

Let the system state at time  $t$  be denoted as  $s_t$ , represented by a feature vector derived from LLR measurements. The action  $a_t$  corresponds to the agent's choice, such as modifying a bit or adjusting a decoding parameter. The decoder's objective function can be mathematically expressed as

$$J(\theta) = E_{\pi_\theta}[R_t] = E_{\pi_\theta} \left[ \sum_{k=0}^{\infty} \gamma^k r_{t+k} \right] \quad (4)$$

where  $\theta$  represents the NN parameters of the agent (Actor and Critic weights in the Policy Network),  $\gamma$  is the discount factor controlling the learning rate, and  $r_t$  is the immediate reward (e.g., reduction in errors).

Parameter updates are performed via the Actor-Critic algorithm, formalized as

$$\theta \leftarrow \theta + \alpha \nabla_{\theta} \log \pi_{\theta}(a_t | s_t) (R_t - V(s_t)) \quad (5)$$

Here,  $\pi_{\theta}(a_t | s_t)$  defines the policy, i.e., the probability of selecting action  $a_t$  in state  $s_t$ ,  $\alpha$  is the learning rate controlling the magnitude of weight updates, and  $\nabla_{\theta} \log \pi_{\theta}(a_t | s_t)$  is the gradient of the log-policy indicating how to adjust weights to maximize the expected reward. The update rule performs gradient ascent to maximize the expected reward, so the negative sign used in loss minimization formulations is not required.

The weight update for a neural layer  $l$  in the Actor network is given by:

$$\begin{aligned} \theta \{W^{(l)}, b^{(l)}\}, \quad l = 1, \dots, L, \\ W_{t+1}^{(l)} = W_t^{(l)} + \alpha \delta^{(l)} (h^{(l-1)})^T, \\ b_{t+1}^{(l)} = b_t^{(l)} + \alpha \delta^{(l)} \end{aligned} \quad (6)$$

where  $W^{(l)}$  is the weight matrix,  $b^{(l)}$  is the bias vector, Actor determines the action selection given state  $s_t$ , and Critic evaluates the value of the state or state-action pair,  $h^{(l-1)}$  is the input (activation) from the previous layer,  $\delta^{(l)}$  is the gradient of the objective function with respect to the pre-activation of layer  $l$ ,  $\alpha$  is the learning rate controlling the update magnitude,  $t$  denotes the training iteration (episode index).

The Actor and Critic are implemented as lightweight fully connected neural networks (two hidden layers). An example layer representation for the Actor is:

$$a_t = \text{soft max}(W^{(l)} s_t + b^{(l)}) \quad (7)$$

where  $s_t$  is the feature vector from the Feature Extractor (see the schematic in Fig. 3),  $W^{(l)}$  and  $b^{(l)}$  are the parameters of  $\theta$  that will be updated via gradient descent, and  $a_t$  represents the action probability distribution (for the decoder, this indicates which bits to correct, which iterations to activate, etc.).

In this hybrid intelligent decoder, all parameters  $\theta$  – weights and biases of the NN – are optimized through the reward signal to enable effective decoding under challenging interference conditions, without hard-coded rules. These parameters define how the agent processes the input state vector  $s_t$  derived from LLRs and decides on actions  $a_t$  (bit corrections, decoding path choices, etc.). During training, these parameters are updated via gradient methods to maximize expected long-term reward, thereby encoding an adaptive strategy for the agent to dynamically adjust to channel variations.

The policy mechanism functions as follows: if the policy  $\pi_{\theta}$  indicates “perform action  $A$  with 80% probability and  $B$  with 20%,” and action  $A$  yields a positive

reward, the model updates to make action  $A$  even more likely in the future. This is implemented by taking the gradient of the log-policy, multiplying by the advantage (actual reward minus expected reward), and updating the Actor weights to reinforce effective strategies. From a decoding perspective, this allows the Actor to adapt to increased noise, make strategic decisions beyond simply correcting erroneous bits, and learn from successful examples rather than memorizing correct outcomes.

The novelty of the proposed approach for intelligent decoding of 5G/6G signals lies in: 1) Combining DRL with classical Soft-Decision decoding, enabling flexible adaptive strategies; 2) Allowing the system to adjust to channel variations (fast fading, ISI, noise) without complete retraining; 3) Providing improved convergence and interpretability compared to purely NN-based decoders [12].

We present a systematic overview of the application of the proposed decoder to specific coding methods. For LDPC codes, the DRL agent is capable of dynamically reordering message updates within the BP decoding algorithm or controlling the depth of iterations, optimizing decoding efficiency based on the current channel conditions. For P-C, the agent can guide path selection within CA-SCL decoding or adjust probabilistic decisions for bit flips in Fast Simplified Successive Cancellation (Fast-SSC), enabling more informed and adaptive decoding strategies.

Regarding the Actor-Critic policy in the proposed decoder, it adapts to channel environment conditions, with the DRL agent learning to make decisions based on the type of interference (noise, ISI, etc.). It implements strategic learning – the decoder builds an action policy that reduces future errors rather than focusing solely on immediate, local mistakes. The system supports soft-decoding, allowing the agent to influence decisions within the classical decoder, including LLR adjustments and path selection. Finally, the architecture is flexible; the Actor and Critic modules can be implemented using various NN types (DNN, GNN), making the system suitable for deployment on FPGA or Application-Specific Integrated Circuits (ASIC) platforms [19, 24].

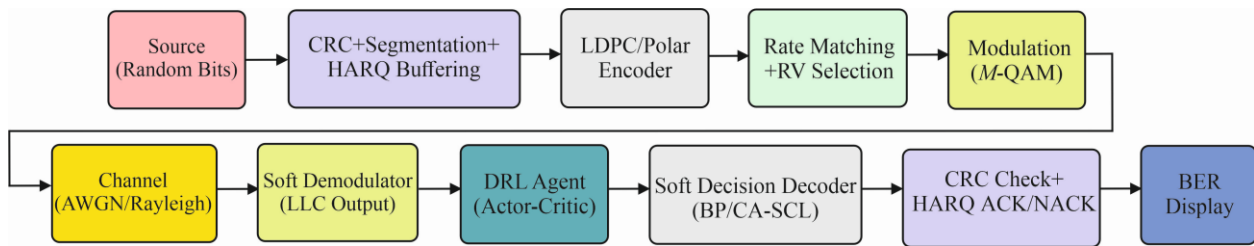
The DRL+Soft-Decision Decoder architecture represents a promising approach for next-generation networks. Its flexibility, adaptability, and support for multiple code types make it a competitive alternative to conventional decoding schemes. The primary objective of this intelligent decoder is to develop a strategy that minimizes long-term decoding errors. The uniqueness of

the hybrid decoder lies in its integration of two conceptually distinct approaches: classical Soft-Decision decoding (BP or CA-SCL), which ensures accuracy through LLR-based algorithms, and DRL, which provides adaptive decision-making based on the current system state. This hybridization enables the system not only to perform decoding but also to optimize decoding parameters online, dynamically adjusting to changing 5G/6G channel conditions. Regarding AI-related challenges such as overfitting and robustness, the proposed architecture allows the DRL agent to employ regularization or exploration strategies (for example,  $\epsilon$ -greedy policies balancing exploration and exploitation [26]). During training, the  $\epsilon$ -greedy algorithm can determine bit-flipping decisions within the LLR vector. Robustness measures include feedback loops, weight constraints, gradient normalization, and control of parameters  $\gamma$  and  $\alpha$  in Eqns. (4), (5). In future research, the plan is to leverage meta-learning or transfer learning to generalize across different channel types, enabling the agent to adapt to new noise, interference, or delay conditions with minimal policy adjustments.

## 4 Experimental evaluation of intelligent decoding for robust 5G/6G codes

### 4.1 Simulation framework of the 5G physical channel with intelligent decoding

The 5G physical layer (PHY) Fig. 4, particularly the PDSCH (Physical Downlink Shared Channel), serves as the backbone for downlink user data from the gNB to the UE [27]. Its architecture supports high throughput and flexibility, integrating MIMO, adaptive modulation schemes (from QPSK up to 1024-QAM) [28], and advanced error-correcting codes, including LDPC for large transport blocks and P-C for short control messages such as Physical Downlink Control Channel (PDCCH) and Physical Broadcast Channel (PBCH) [29]. Standard PHY procedures – such as transport block segmentation, CRC protection, rate matching, redundancy version selection, and Hybrid Automatic Repeat Request (HARQ) retransmissions – ensure reliability and efficient use of radio resources. Synchronization and channel estimation are facilitated through Primary/Secondary Synchronization Signals (PSS/SSS) and Demodulation Reference Signals (DM-RS) signals [10], while Acknowledgement/Negative Acknowledgement (ACK/NACK) signaling manages retransmissions to maintain robust communication (see Fig. 4).



**Fig. 4.** Structural diagram of the 5G PDSCH physical channel architecture with integrated DRL+Soft intelligent decoding mechanism

Building upon this foundation (see Fig. 4), a simulation model was developed in MATLAB to study the integration of a hybrid DRL+Soft-Decision decoder for adaptive error correction. The model maintains a simplified yet representative structure of the 5G PHY, balancing computational efficiency with realism. Key elements include random bit generation as the information source, coding via LDPC or Polar encoders,  $M$ -QAM modulation, channel impairments (AWGN and Rayleigh fading), soft demodulation producing LLRs, and an intelligent DRL agent operating in an Actor-Critic configuration. In this framework, LDPC codes use iterative BP, and P-C leverage CRC-Aided SCL decoding. The DRL agent observes LLRs and other channel characteristics, dynamically optimizing decoding parameters such as the number of iterations, modulation type, or redundancy version in real time. To focus on the study of adaptive decoding, mechanisms like HARQ buffering, dynamic Redundancy Version (RV) selection, and interleaving are abstracted, while soft combining preserves the benefit of previous transmission attempts. Performance metrics [28], including BER and BLER, provide feedback for the DRL agent's reward function, enabling learning and system adaptation under varying channel conditions.

This hybrid modeling approach allows experimental evaluation of LDPC and P-C and the performance of the intelligent DRL agent, demonstrating how real-time adaptation at the PHY level can enhance throughput, reduce latency, and minimize unnecessary retransmissions while preserving the essential structure and key mechanisms of the 5G physical channel.

#### 4.2 Requirements for the DRL agent

The DRL agent was implemented using the Actor-Critic framework (see Fig. 2). A shallow NN with 2-3 hidden layers proved sufficient for the decoding task, where the state is modelled as a bit vector and actions are defined over bitwise operations – flipping or preserving individual bits. The Actor (Policy Network) generates action strategies, specifying which bit operations or transitions to perform, while the Critic (Value Network) evaluates the quality of the current state or state-action pair.

Key hyperparameters include a learning rate of  $\alpha = 0.001$  and a discount factor of  $\gamma = 0.95$ . The learning rate controls how quickly the network updates its weights during gradient descent, ensuring stable and gradual learning. The discount factor balances the importance of future versus immediate rewards. A value of  $\gamma = 0.95$  allows the agent to account for long-term effects of its actions rather than focusing solely on immediate outcomes. The agent interacts with the simulation environment over 200 to 500 episodes, where each episode corresponds to a full decoding attempt of a transport block. This range provides sufficient training for the agent to develop effective bit-improvement strategies, using feedback from the decoding process to refine its policy over time. Reward signals are computed based on CRC verification and the resulting BER. Successfully passing a CRC check yields a positive reward (+1), while a failed check results in a negative reward (-1). Additionally, lower bit-error rates increase the Reward, guiding the agent to improve overall decoding accuracy. Mathematically, this can be expressed as:

$$Reward = k \cdot f(CRC, BER) \quad (8)$$

where  $k$  is a scaling factor.

This configuration provides a simple yet effective framework for the DRL agent, enabling adaptive decision-making during decoding. By leveraging feedback from CRC and BER [24], the agent continuously optimizes its strategy to correct bits and improve decoding performance in real time. In our simulations, the standard 24-bit CRC, as defined in 5G transport blocks, is used to determine the reward for the DRL agent.

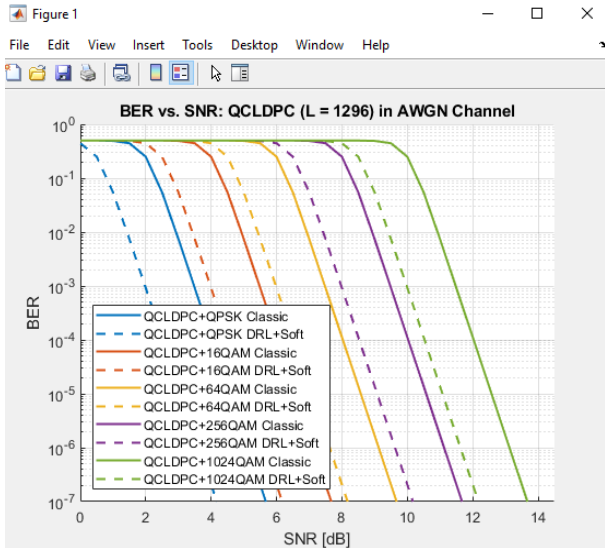
#### 4.3 Experimental evaluation of DRL-based intelligent decoding performance for QC-LDPC and polar codes in AWGN and Rayleigh channels

To evaluate the efficiency of the proposed hybrid DRL-based decoding architecture (DRL+Soft-Decision), simulations were conducted for Quasi-Cyclic LDPC (QC-LDPC) codes and P-C in both AWGN and Rayleigh fading channels. The primary objective is to compare the performance of conventional decoders with

the intelligent DRL-assisted system in terms of BER versus SNR [10]. These results highlight the potential of intelligent decoding strategies in 5G systems, particularly for energy-constrained devices.

The simulations considered QC-LDPC codes of various lengths, including 648, 1296, and 1944 bits, which are relevant for different 5G scenarios such as URLLC, massive Machine-Type Communications (mMTC), and enhanced Mobile Broadband (eMBB).

P-C of lengths 512, 1024, and 2048 bits were also analyzed, covering both short packets for URLLC/IoT and longer blocks for eMBB applications. The DRL agent, implemented using the Actor-Critic framework, interacts with the decoding process by optimizing bit-level decisions based on reward feedback derived from CRC checks and BER evaluation. This approach consistently yields an energy gain of approximately 1 to 1.5 dB, effectively reducing the required SNR for a given BER.

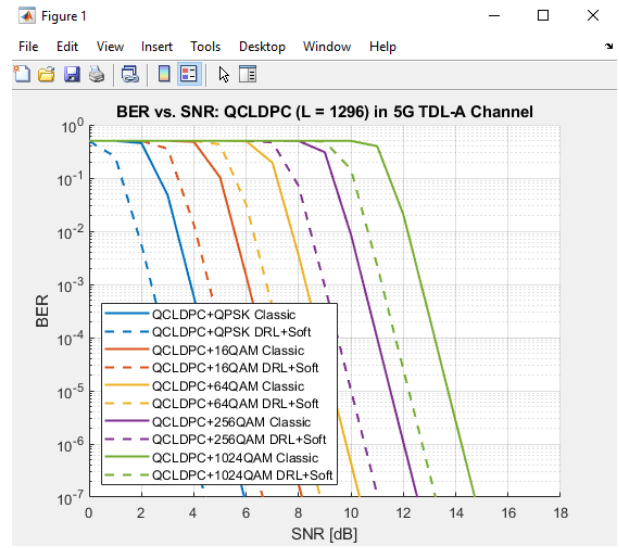


**Fig. 5.** BER vs SNR performance curves for QC-LDPC code with code length 1296 bits in AWGN channel simulation

Figure 5 presents BER vs SNR curves for a QC-LDPC code of length 1296 in an AWGN channel, comparing conventional Soft-Decision decoding with the proposed DRL-enhanced approach.

Figure 6 shows the performance of the same QC-LDPC code in a Rayleigh (Frequency-selective Rayleigh fading (3GPP 38.901 [29]) TDL-A) fading channel. Despite stochastic amplitude fluctuations, the DRL-assisted decoder maintains a notable energy gain (~1.5 dB), confirming its ability to adapt to multipath fading environments.

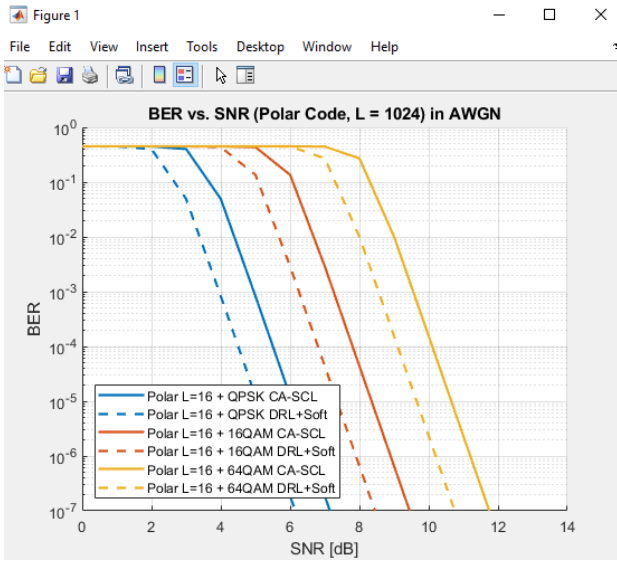
Figure 7 illustrates BER vs SNR results for a P-C of length 1024 in an AWGN channel. The comparison between standard CA-SCL decoding and the DRL+Soft scheme highlights the consistent energy advantage of the intelligent decoder, particularly under moderate to high-order modulations. This demonstrates the feasibility of employing DRL-based decoding for short- and medium-length codes in high-reliability 5G applications.



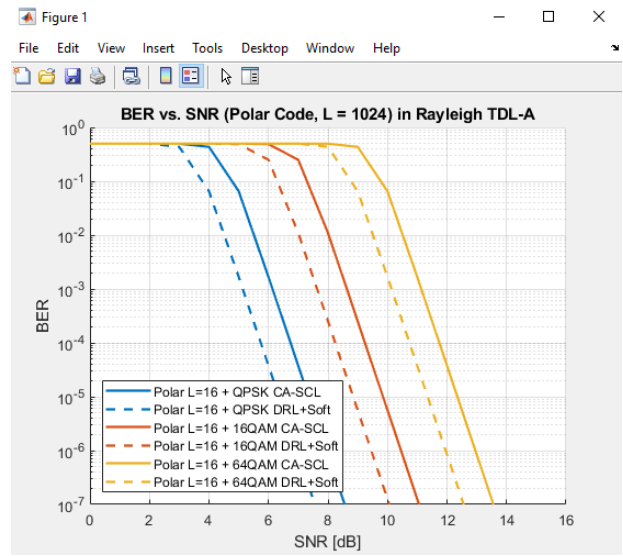
**Fig. 6.** BER vs SNR performance curves for QC-LDPC code with code length 1296 bits in Rayleigh channel simulation

Figure 8 depicts the performance of the same P-C in a Rayleigh (TDL-A) fading channel. The intelligent decoder preserves a gain of approximately 1 dB across different coding rates ( $R=0.5$  and  $R=0.75$ ), validating its robustness under realistic multipath conditions and emphasizing the practical benefits for energy-constrained IoT devices, URLLC scenarios, and latency-sensitive applications.

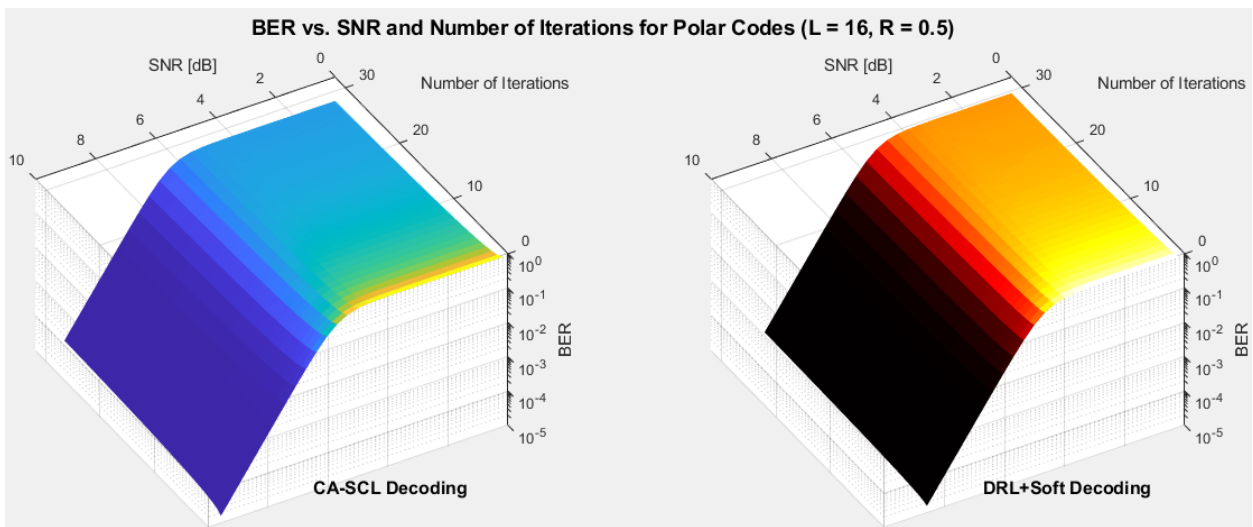
Overall, these selected results demonstrate that DRL-assisted hybrid decoding consistently improves BER performance across different code types, lengths, and channel conditions, providing both technical and practical advantages for 5G and beyond communication systems.



**Fig. 7.** BER performance curves for 1024-bit P-C in AWGN channel, comparing CA-SCL decoding ( $L=16$ ) and hybrid DRL+Soft decoding



**Fig. 8.** BER versus SNR curves for 1024-bit P-C in Rayleigh TDL-A channel, comparing CA-SCL and DRL+Soft decoding

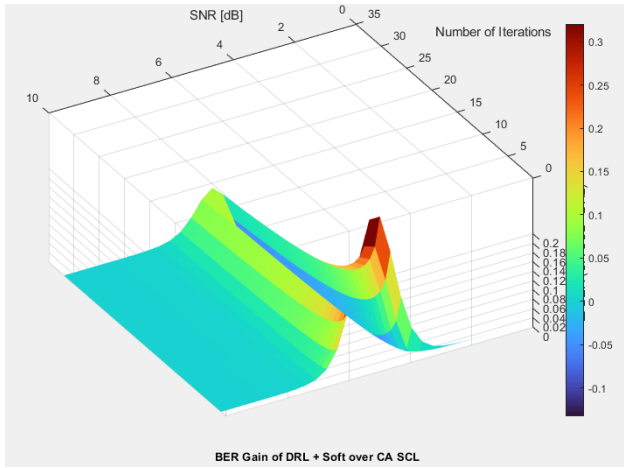


**Fig. 9.** 3D BER surfaces versus number of decoding iterations comparing classical and intelligent decoders for polar code

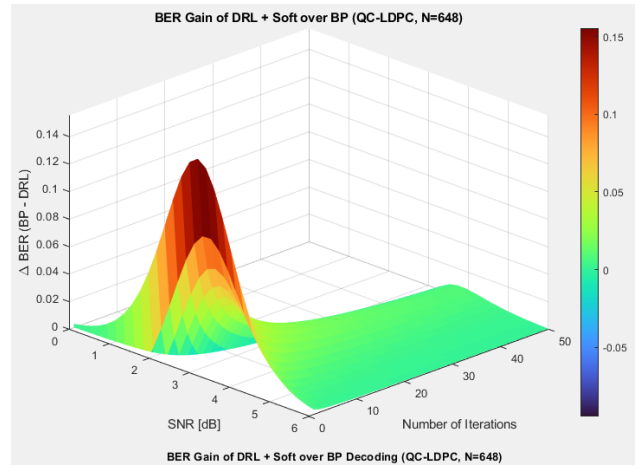
Figures 9 to 11 present 3D BER surfaces as a function of decoding iterations, comparing classical and intelligent decoders. Specifically, Fig. 9 illustrates a typical scenario for P-C with  $L=16$ ,  $R=0.5$ , and highlights 32 decoding iterations.

Figure 10 shows a surface representing the difference between BER of classical CA-SCL and intelligent DRL+Soft decoders. This graph clearly highlights regions where DRL decoding outperforms. Axes are defined as follows: X-axis (SNR [dB]) – SNR, with

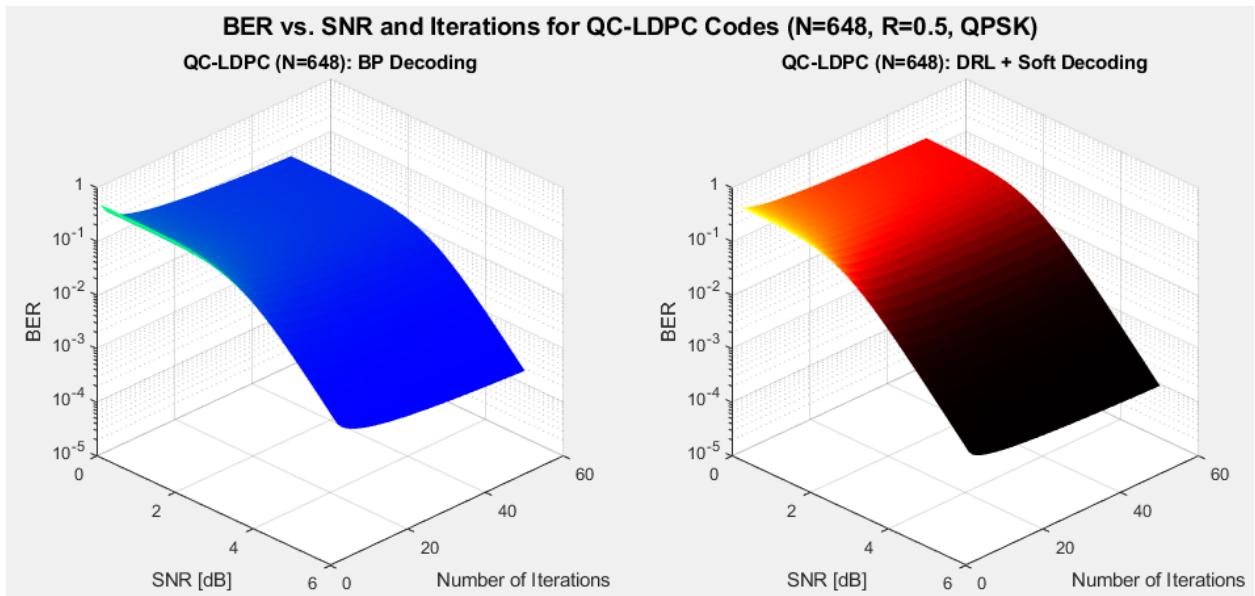
higher values indicating better signal quality; Y-axis (Number of Iterations) – decoding iterations; Z-axis ( $\Delta\text{BER} = \text{BER}_{\text{CA}} - \text{BER}_{\text{DRL}}$ ) – difference in bit error rate between classical CA-SCL and intelligent DRL+Soft decoders. Cool colors (blue to green) correspond to small or negative BER differences, while warm colors (yellow, orange, red) indicate significant DRL+Soft gains, i.e., lower error probability compared to CA-SCL. Notably, prominent regions of DRL advantage are observed at moderate SNR (4 to 7 dB) and low iterations (5 to 15), where decoding efficiency is most critical.



**Fig. 10.** Surface showing  $\Delta\text{BER}$  difference between classical CA-SCL and intelligent DRL+Soft decoders for P-C



**Fig. 11.** 3D surface showing  $\Delta\text{BER}_{\text{gain}} = \text{BER}_{\text{BP}} - \text{BER}_{\text{DRL}}$  for 648-bit QC-LDPC (5G standard) comparing BP and DRL+Soft decoders



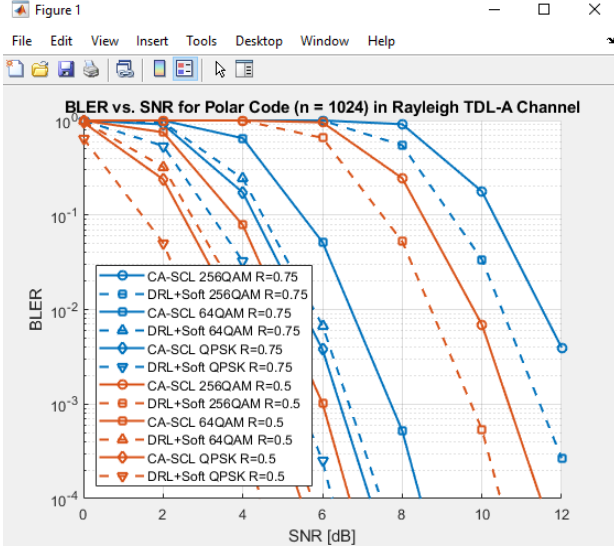
**Fig. 12.** 3D BER visualization for QC-LDPC code decoded using classical BP and intelligent DRL+Soft decoder (script parameters adapted for 648-bit 5G LDPC with QPSK)

At very low SNR (left side of the graph), both decoders perform poorly, so gains are minimal. As SNR increases, DRL gains become more pronounced. Higher decoding iterations reduce BER for both decoders, but DRL+Soft improves faster, resulting in increased  $\Delta\text{BER}$  at the top of the graph. Maximum BER difference occurs in the mid-to-high SNR range (~5 to 10 dB) and iterations above 10-15, where DRL+Soft leverages its adaptive strategies most effectively.

Figure 11 illustrates the 3D surface of  $\Delta\text{BER} = \text{BER}_{\text{BP}} - \text{BER}_{\text{DRL}}$  for the 648-bit QC-LDPC code (5G standard), comparing BP decoder against DRL+Soft. Z-axis values represent BER gain (lower errors achieved

by DRL+Soft). Light-green areas indicate small gains (low SNR or few iterations), while yellow/red areas indicate significant DRL+Soft advantage. The simulation considered 50 iterations, a typical BP decoding limit.

Figure 12 demonstrates the bit error rate difference between classical BP decoding and intelligent DRL+Soft. Positive values (warm colors: yellow, orange, red) indicate better performance of DRL+Soft. Red regions highlight areas with significant DRL gains at SNR~2 to 4 dB and 10 to 30 iterations, where DRL outperforms BP by reducing BER faster without extra iterations. At very low SNR (<1 dB), both decoders



**Fig. 13.** BLER vs SNR curves for P-C with block length  $n=1024$  in Rayleigh fading channel

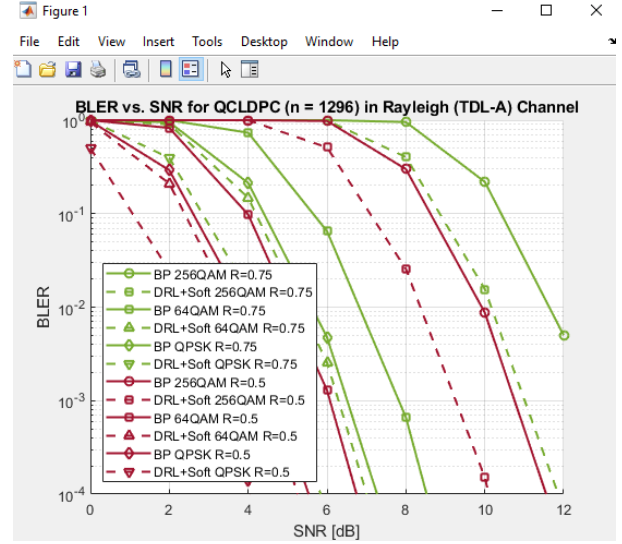
show high error rates, and gains are minimal. At high SNR ( $>5$  dB) with many iterations, both decoders achieve low BER, so DRL advantage diminishes.

Similarly, Fig. 12 presents the 3D BER surfaces for QC-LDPC coding. In this simulation, Base Graph 2 (BG2) from 5G NR [29], a code rate of  $R = 0.5$ , and QPSK modulation were used.

These results show that DRL+Soft decoding is most effective in critical SNR zones, where classical BP has not yet stabilized. The DRL agent adapts quickly based on feedback (BER or CRC), while BP updates messages iteratively in a fixed manner. This enables DRL+Soft to reach lower BER values with fewer iterations, reducing decoding latency and energy consumption without sacrificing accuracy. The comparison between the two surfaces clearly demonstrates that DRL-based decoding converges faster, especially at moderate SNR values (2 to 4 dB), making it advantageous in resource-constrained scenarios and environments requiring rapid channel adaptation.

In 5G NR, the reliability of transmission is typically assessed by the BLER – the probability that a transport block or codeword is decoded incorrectly. BLER is a key metric in link adaptation, directly defining the required SNR to ensure target reliability levels (e.g.,  $10^{-2}$  in standard 5G configurations 3GPP TS 38.214).

Figure 13 presents BLER vs. SNR curves for P-C of length 1024 under both AWGN and TDL-A Rayleigh fading channels.



**Fig. 14.** BLER vs SNR curves in Rayleigh (TDL-A) channel for QC-LDPC ( $n=1296$ ), comparing BP decoding and DRL+Soft approach

The proposed DRL+Soft decoder demonstrates a consistent gain of about 1.0 dB in AWGN and 1.2-1.3 dB in Rayleigh fading compared to classical CA-SCL ( $L=16$ ). The improvement is especially evident in the critical BLER region ( $10^{-2}$ - $10^{-3}$ ), where enhanced reliability ensures more robust operation in control signaling and IoT scenarios with short block lengths. Fig. 14 shows BLER curves for QC-LDPC codes of length 1296 (BG2) under the same channel conditions. Due to their longer block length, LDPC codes achieve steeper BLER slopes, approaching near-capacity performance. With DRL+Soft decoding, the system achieves an additional 1.5 dB SNR gain over standard BP decoding, both in AWGN and Rayleigh channels. This improvement translates into significantly lower error floors, which is critical for eMBB and URLLC applications requiring high reliability.

In both code families, DRL-enhanced decoding provides a consistent SNR gain of 1.0 to 1.5 dB, independent of channel conditions. This margin corresponds to either reduced transmission power for the same BLER target or extended coverage at fixed power. Consequently, DRL-based intelligent decoding offers practical advantages for diverse 5G/6G scenarios, from energy-constrained IoT devices to high-throughput broadband and ultra-reliable low-latency communications.

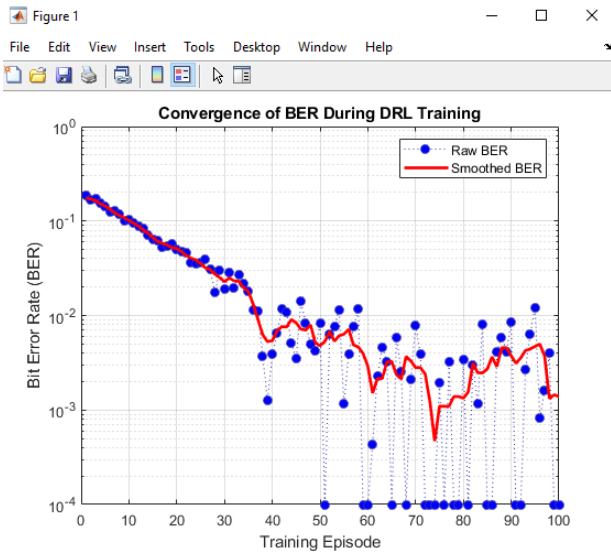


Fig. 15. BER convergence curve versus training episode

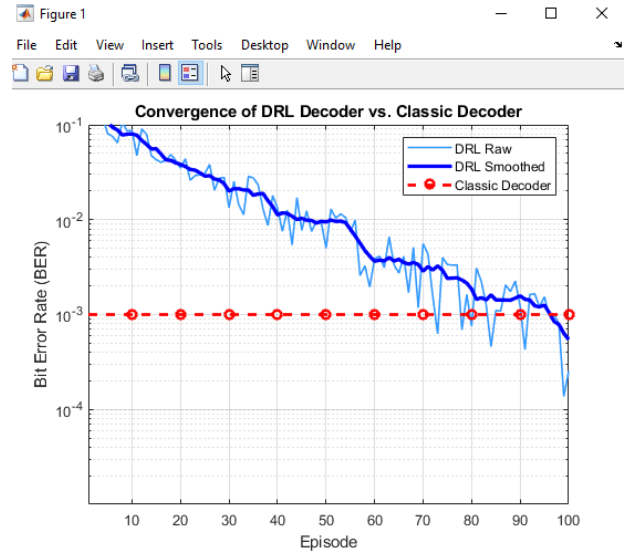


Fig. 16. BER comparison between DRL decoder and classical decoder

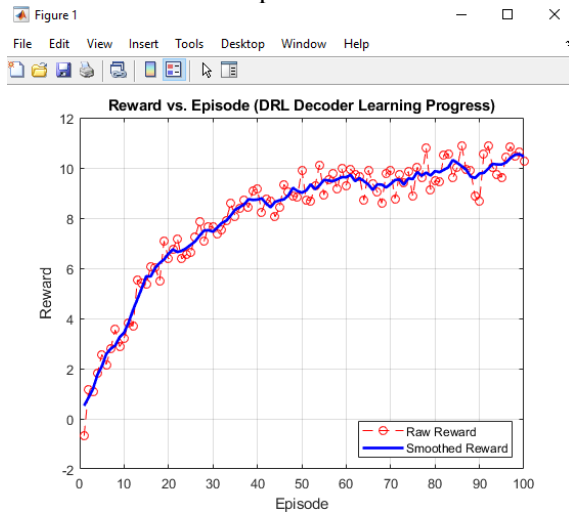


Fig. 17. Reward versus episode

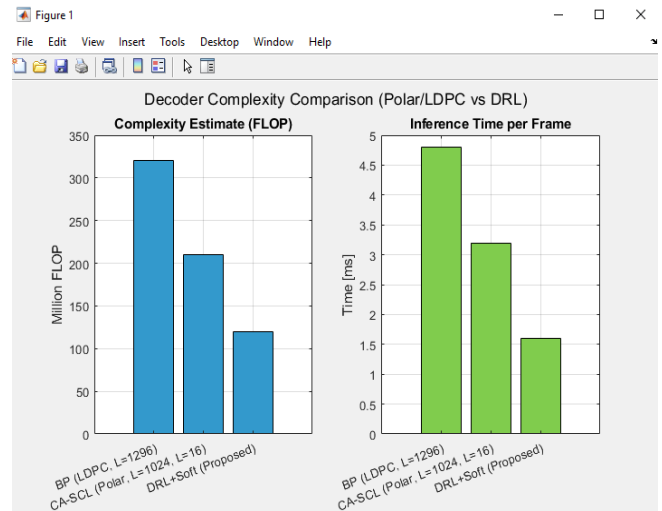


Fig. 18. Computational efficiency and latency (FLOP and inference time)

We present a detailed evaluation of an intelligent decoder based on deep reinforcement learning (DRL+Soft), compared with traditional decoding algorithms such as BP for LDPC codes and CA-SCL for P-C. The assessment concentrates on three principal aspects: decoding performance (BER), agent learning speed, and computational efficiency. Unlike conventional decoders, the DRL-based decoder does not rely on a fixed procedure, instead, it autonomously learns an optimal decoding strategy for diverse channel conditions, offering new opportunities for adaptive 5G and 6G communication systems. To clearly demonstrate the performance of the proposed approach, several key figures are presented.

Figure 15 shows the BER convergence curve versus training episodes, highlighting the progressive reduction of bit error rate as the DRL agent trains. Both Raw BER (fluctuating data) and Smoothed BER (trend line) are

depicted, providing insight into learning speed and model stability.

Figure 16 compares the BER performance of the DRL decoder with classical BP and CA-SCL decoders, emphasizing the advantage of DRL+Soft in terms of stability and lower BER under identical SNR conditions, illustrating its practical benefits. The expected (reference) bits are internally available from the encoder within the environment, allowing bit-wise comparison for BER and reward computation. Thus, the bidirectional feedback in Fig. 16 reflects internal reward evaluation rather than an external input.

Figure 17 also presents reward dynamics versus training episodes, demonstrating the agent’s learning progress through increasing reward values. The Smoothed Reward captures the overall trend, while Raw Reward reflects variability in early episodes. The reward is derived from the bit-wise accuracy between the

decoded output and the transmitted codeword. Hence, increasing reward values in Fig. 17 reflect improved bit-level decoding performance. Figure 18 illustrates computational efficiency and latency, showing FLOP (floating-point operations) and inference time comparisons between DRL+Soft and classical decoders. The DRL decoder requires only 120 million FLOP, compared to 320 million for BP, making it approximately 2.5 times more computationally efficient. Increasing the number of neurons, layers, or iterations increases computational cost proportionally. Inference time, representing the duration to process a single data block from input to output, is reduced from 4.8 ms (BP) to 1.6 ms (DRL), enabling faster decoding, lower PHY-layer latency, and improved quality of service (QoS)—an essential advantage for high-demand 5G URLLC and IoT scenarios [30].

Overall, the presented figures collectively demonstrate the advantages of the DRL+Soft decoder. Figure 15 confirms rapid convergence and stability in BER reduction, indicating effective agent learning. Figure 16 highlights that DRL+Soft consistently achieves lower BER than classical BP or CA-SCL decoders under identical SNR conditions, emphasizing its practical reliability.

Figure 17 shows steadily increasing rewards, reflecting the agent's ability to adapt its decoding strategy over time. Figure 18 demonstrates substantially lower computational complexity and inference latency, which is critical for real-time applications. Together, these results confirm that the proposed DRL-based decoder not only improves error performance but also ensures faster, resource-efficient decoding, making it highly suitable for demanding 5G and emerging 6G scenarios, including URLLC, massive IoT, and energy-constrained devices.

## 5 Conclusion

This work presented a comprehensive investigation of an intelligent decoding methodology for LDPC and P-C based on deep reinforcement learning (DRL+Soft), with a focus on performance evaluation under realistic 5G scenarios. The proposed DRL decoder demonstrates clear advantages over classical decoding schemes such as BP (for LDPC) and CA-SCL (for P-C) across multiple performance metrics, including bit error rate (BER), computational efficiency, and adaptability to diverse channel conditions.

Experimental results show that the DRL+Soft decoder rapidly converges to a low BER, achieving stabilization at approximately  $10^{-4}$  after 40 to 60 training episodes, significantly outperforming classical decoders, which typically plateau around  $BER \sim 10^{-3}$  under identical SNR conditions. The analysis of reward dynamics

confirms effective learning by the DRL agent, while the average number of iterations required to reach acceptable BER ( $<10^{-3}$ ) decreases from 15 to 30 in early episodes to around 5 in later episodes, demonstrating accelerated adaptation to channel conditions.

From a computational standpoint, the DRL+Soft decoder requires only  $\sim 120$  million FLOPs per decoding block, compared to  $\sim 320$  million for the BP decoder, representing a potential  $2.5\times$  improvement in efficiency. Inference time measurements indicate that the proposed decoder processes data blocks in approximately 1.6 ms, versus 4.8 ms for BP and 3.2 ms for CA-SCL, ensuring reduced latency critical for URLLC and low-power IoT applications. Additionally, the DRL+Soft decoder exhibits enhanced robustness against various noise types, including AWGN, impulsive noise, and phase distortions, with observed gains of up to 2 dB in effective SNR for maintaining comparable BER, highlighting its potential for high-density or interference-prone environments such as smart factories and smart cities.

The practical implications of these findings for 5G networks [31] are substantial: lower BER and faster convergence translate into higher reliability for URLLC and eMBB services, while reduced computational load and energy consumption are crucial for mobile and IoT devices. Looking forward, the proposed DRL-based decoding methodology holds significant promise for 6G systems. Specifically, the proposed DRL+Soft decoders could serve as the core of cognitive receivers, enabling real-time adaptation of decoding policies. Their experimentally validated robustness against unpredictable noise makes them well-suited for high-density device deployments and interference-heavy scenarios, such as Smart Cities or Smart Factories. The observed reduction in FLOPs directly translates into lower energy consumption, addressing a critical requirement for 6G-IoT applications. Furthermore, DRL agents can be retrained or updated without any hardware modifications, allowing seamless integration with evolving system models and ensuring long-term operational viability. Overall, the DRL+Soft decoder combines theoretical novelty with substantial practical value, offering a forward-looking solution for both contemporary 5G networks and emerging 6G telecommunication systems.

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