

A Scalable Graph Neural Network Decoder for Advanced Satellite Communications

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Introduction

Satellite communication systems, with the nature of long distance transmission and high attenuation level, face the challenge of frequent signal interference. To improve the system reliability, channel coding technology is utilized to combat channel impairments and control transmission errors in the process of satellite communication. For example, the CCSDS TC Recommendation [1] chose BCH codes and LDPC codes for uplink coding.

In modern satellite communication, traditional coding methods struggle due to complex and unreliable environments. Researchers are actively seeking optimal coding schemes that are accurate, flexible, and simple. Deep learning techniques have shown promise in improving decoding, but many studies face the challenge of increased neural network complexity as codewords grow longer.

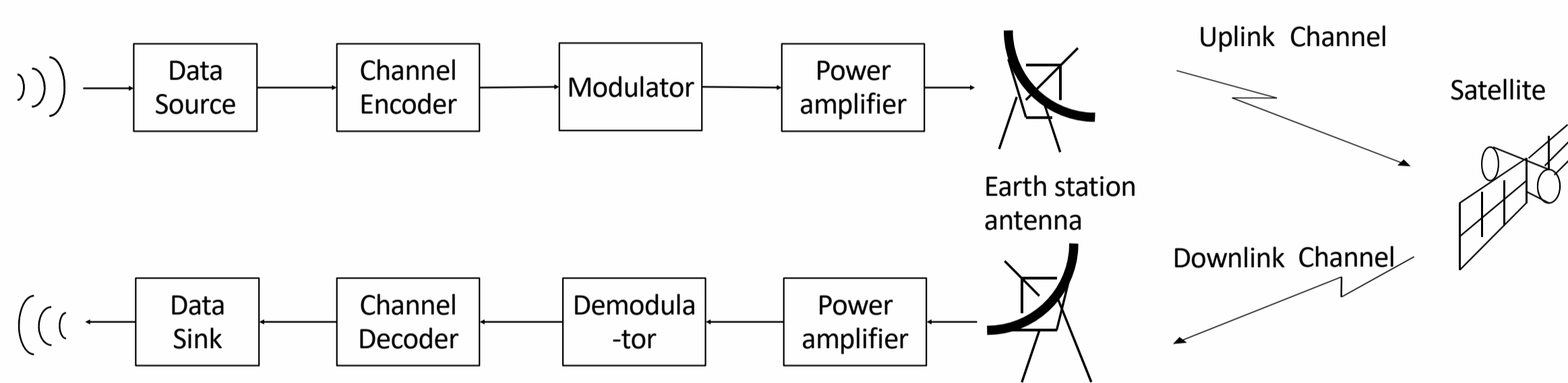


Figure 1: Basic schematic diagram for satellite communication.

From the point view of scalability, we utilize the scalable Graph Neural Network (GNN) technique to develop a novel channel decoding method, allowing a single neural network structure to decode any block code. This single trained GNN decoder is applicable across various block lengths and code rates.

Aims

Develop a novel GNN-based channel decoding algorithm with better error correcting capability, improved scalability, and lower training complexity, to enhance the accuracy and reliability of satellite communication systems in physical layer.

Methods

GNNs for Channel Decoding

- GNN is a class of DL methods and is designed to process graph structured data.
- Linear block codes can be graphically represented as the Tanner graph. n variable nodes in the Tanner graph correspond to n codeword bits.
- The channel decoding problem is in fact a binary node classification task on the Tanner graph.
- The GNN-based decoder can finally obtain estimated codewords from node embeddings.
- In each iteration, a variable node in GNN is assigned a hidden embedding, which is updated based on the edge messages on the Tanner graph.

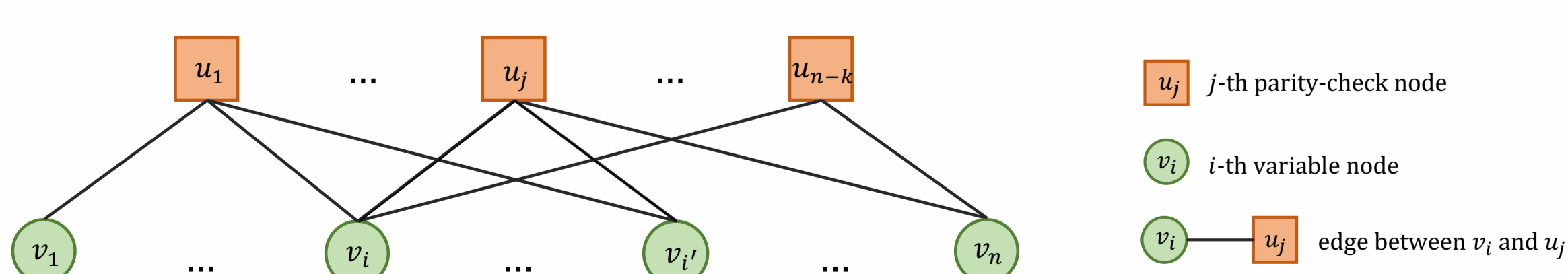


Figure 2: A bipartite Tanner graph.

Training of GNN

- The goal of the training phase is to find an optimal GNN that minimizes the difference between the transmitted codeword and the estimate output by the decoder.
- During the training phase, GNN parameters are updated utilizing the Adam optimizer with a given learning rate.

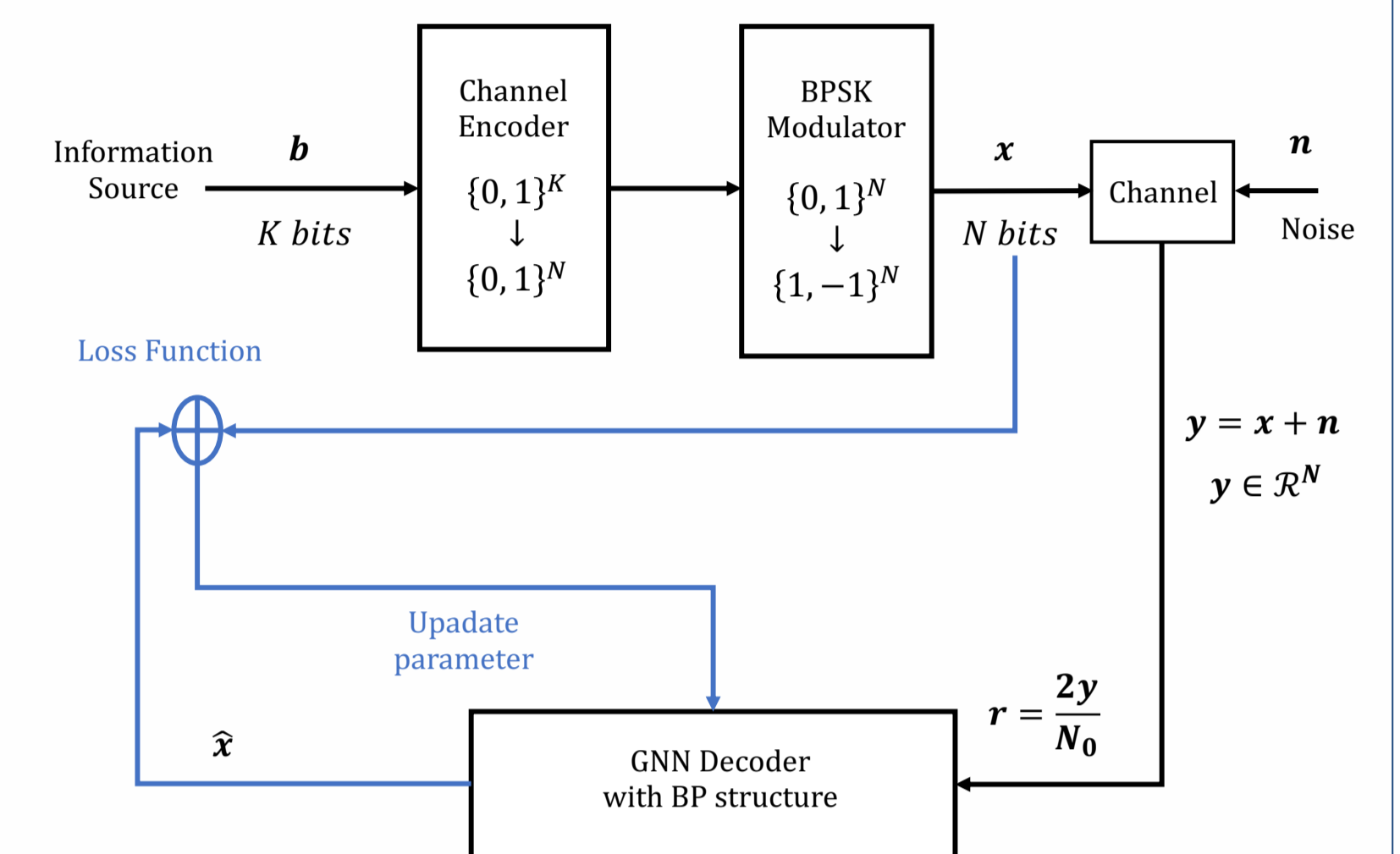


Figure 3: The end-to-end training system.

Results

We evaluate the decoding performance for BCH and LDPC codes. The model hyperparameters are provided in the table below. Figure 4 and Figure 5 show the bit error rate (BER) results for the learned decoders. Simulation results show that GNN decoder can improve BER performance compared to the conventional BP and the NBP decoder for short BCH and LDPC codes.

We also verify the GNN decoders' generalization capability by applying a single trained decoder model directly to process codes with different block lengths and code rates. It shows that the GNN decoder is scalable to the code length and code rate, i.e., a well-trained GNN can be used to decode codes with different parameters without re-training.

Training iterations	Training SNR	Learning Rate	Batch Size
8	1-8 dB	10^{-3} , 10^{-4} , 10^{-5}	2000, 4000

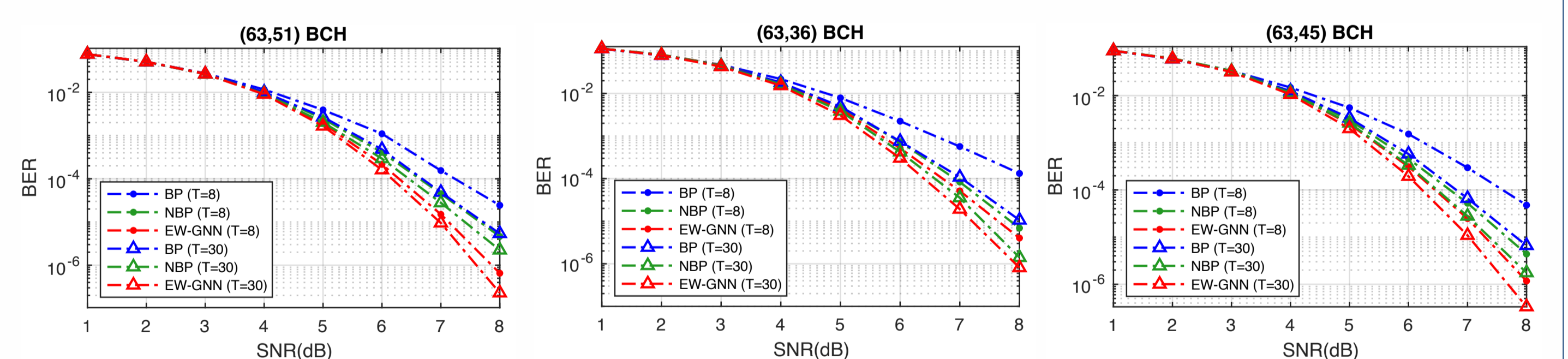


Figure 4: BER performance for BCH codes of length $n = 63$. EW-GNN is only trained with the (63, 51) BCH code and $T = 8$.

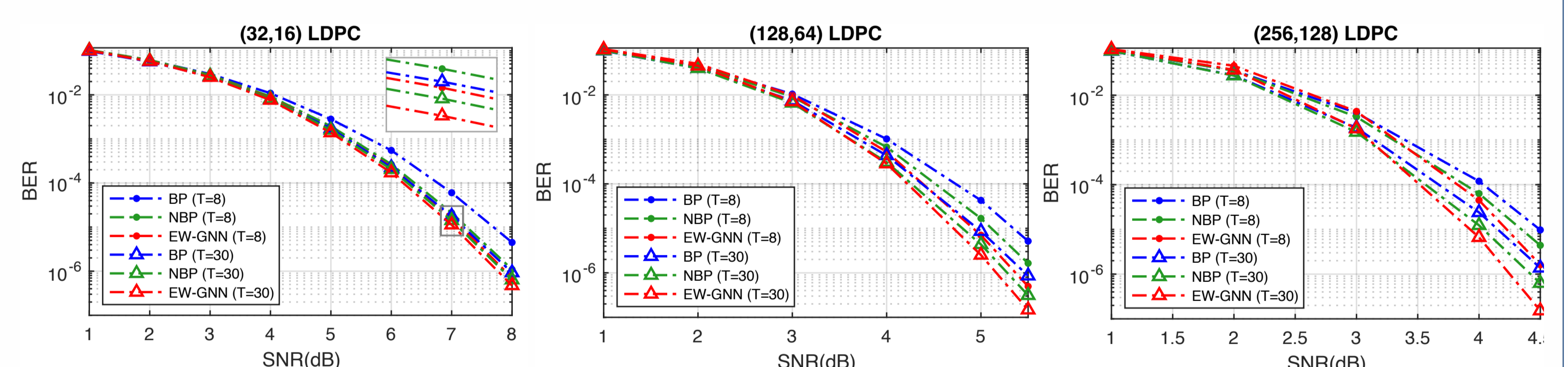


Figure 5: BER performance for LDPC codes at rate 1/2. EW-GNN is only trained with the (32, 16) LDPC code and $T = 8$.

References

- [1] CCSDS, TC Synchronisation and Channel Coding, Washington, DC, USA, Apr. 2022, Blue Book, CCSDS 231.0-B-2.
- [2] Eliya Nachmani, Elad Marciano et.al, Deep learning methods for improved decoding of linear codes. IEEE Journal of Selected Topics in Signal Processing, 12(1):119–131, 2018