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Performance evaluation of polar coded neural demapper based 5G MIMO communication system by varying antenna size

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Abstract This paper proposes a Polar-coded neural damapper based 5G multiple-input multiple-output (MIMO) system for M transmitting and N receiving antenna, operating in a flat fading environment. MIMO is a spatial diversity scheme to improve channel performance and mitigate troubling fading issues in urban environments. A neural network-based smart demapper is considered instead of traditional demapper to improve the system's performance. Researchers have recently focused on developing complex neural network (NN)-based demapper on generating soft information for each transmitted bit. Neural demapper also increases spectral efficiency, meaning a symbol-to-bit demapper with higher complexity. This work considers a Polar-coded MIMO 5G communication system with 2×3, 2×4, 4×6 and 4×16 transmitting and receiving antennas, respectively, to evaluate the system performance under QAM modulation (4-QAM, 16-QAM, 256-QAM) techniques. It is evident from the simulated result that our proposed system performs better for lower-order modulation techniques with an increase in the number of transmitting and receiving antenna.

Keywords: polar code, QAM, neural-demapper, 5G MIMO communication, antenna variation

1. Introduction

Now a day, we move towards the next generation of communication systems with enhanced bandwidth and data rates. The multiple-input multiple-output (MIMO) is the possible solution as it can enhance gains on capacity over the wireless channels (Tse and Viswanath 2005). The fourth-generation (4G) confirmed the success of MIMO systems and the growing importance of recent deployments of the fifth-generation (5G) technology. Early research of the sixth-generation (6G) also represents MIMO systems as a key component for advanced wireless communication systems.

For further performance improvement of the communication system, several researchers proposed introducing a channel coding technique into the MIMO communication system. One of the most popular channel codes is turbo code, which introduces turbo encoding at the transmitter and decoding at the receiver to increase the channel capacity of various wireless communication systems, such as LTE system or other advanced communication system (Dai et al 2003; Ueng et al 2009; Hykin et al 2004).

Hykin et al (2004) define linear and nonlinear TC-MIMO systems where the linear system concatenated the MIMO decoder, e.g., the LMMSE algorithm, with the turbo decoder by processing them separately. However, the error correction is performed based on the soft-decision messages of the turbo decoder (Vucetic and Yuan 2003). Furthermore, the detection and decoding technique is realized jointly by extending the iterative processing principle for the nonlinear TC-MIMO system. In this situation, turbo decoding acts as the error-controlling unit to enhance system performance by reducing error in propagation (Ueng et al 2009; Hykin et al 2004; Vucetic and Yuan 2003). Hence, the above TC-MIMO systems use the turbo coding to enhance the data rates of the communication system close to that of the corresponding channel capacities.

Then, Arikan (2009) proposed polar codes that solves problems related to signal processing, such as source encoding (Hussami et al 2009; Korada and Urbanke 2010), information secrecy (Hof and Shamai 2010), memory channels (Sasoglu and Tal 2016; Shuval and Tal 2017) and other scenarios. Seidl et al (2013) then introduced a 2 M-ary polar-coded modulation scheme to improve the spectral efficiency. Authors (Dai et al 2003) propose a polar-coded MIMO communication system that combines polar coding with the MIMO technique.

With the advancements in artificial inteligency in various research fields, it has also grown the same interest in wireless communications. Recently, several researchers suggested implementing deep neural networks (DNNs) (Neumann et al 2018; Chang et al 2019; Shental and Hoydis 2020; Jeon et al 2021) instead of the functional blocks of the communication system. An author in (Honkala et al 2021) proposed to use of DNN for jointly learning channel estimation, equalization, and LLR demapping

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that are part of the functional blocks of a communication system. Complex neural networks are not frequently feasible as the training time is higher for the large number of trainings parametes. Therefore, for simplicity of operation, Honkala et.al proposed to use LMMSE estimator at pilot location for demapping using neural network.

In this paper, we introduce a polar-coded neural demapper based 5G MIMO communication system with variations in transmitting and receiving antenna sizes. In order to reverse the imperfect channel estimation effect, the learned neural network demapper has been replaced by the Gaussian demapper.

The next section of this paper describes the design of 5G Polar codes, while Section 3 describes the details of polar-coded neural damapper based 5G MIMO communication system. After that, Section 4 shows the simulation results obtained from the proposed system in Section. And finally, Section 5 concluded our work with a conclusion.

2. 5G Polar Code

A polar code is called a linear block error-correcting code. This code is made by multiple recursive concatenation of basic polarization kernel code which transforms the physical channel into virtual external channels. This concatenation generates a channel transformation matrix of the form $\mathrm{G_N} = \mathrm{G}_2^{\otimes n}$, defined by the n −fold Kronecker product of G_2, and that can be recursively calculated as $\mathrm{G_N} = \begin{bmatrix} \mathrm{G_{N/2}} & 0 \\ \mathrm{G_{N/2}} & \mathrm{G_{N/2}} \end{bmatrix}$. While for $\mathrm{n} \to \alpha$ this construction creates channels that are either perfectly noiseless or completely noisy, for smaller values of n the synthetic channels polarization may be incomplete, generating intermediary channels that are only partially noisy.

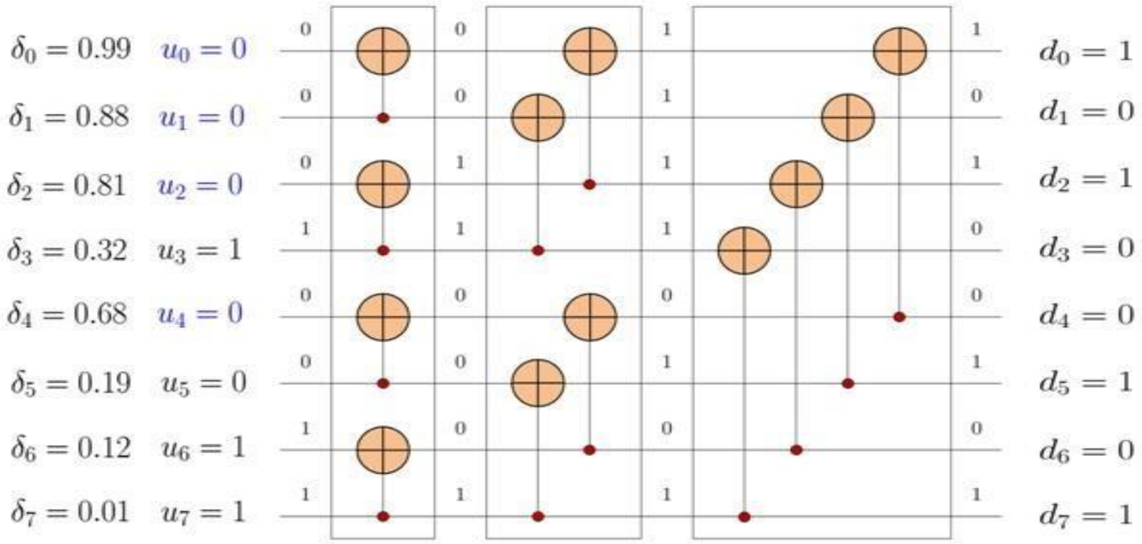

Figure 1 Encoder of (8,4) polar code.

The design of an $(N;\ K)$ polar code is to ensure the K best synthetic channels for providing the highest reliability to transmit the information bits. First it sorts the reliability order and assign the K information bits to the most reliable channels, whose indices create the information set I of the code. The remaining $\boldsymbol{N} - \boldsymbol{K}$ indices form the frozen set $y = \boldsymbol{I}^{\boldsymbol{C}}$ of the code and do not carrying any information. Figure 1 shows the encoder of (8,4) polar code.

3. Neural Demapper for 5G MIMO Communications

3.1 Polar-coded 5G MIMO Communication System

Figure 2 shows the polar-coded 5G MIMO communication system where a neural demapper is used at the receiving side of this system. On the transmitting side, at first the transmitted information is 5G polar encoded, then QAM mapped and finally transmitted through the communication channel. A flat fading channel is considered as the transmission media for this system. On the receiver side, we simply develop a neural network model for QAM demapper by computing log-likelihood ratios (LLRs) on the transmitted bits. The proposed model is benchmarked against 2×3, 2×4, 4×6 and 4×16 transmitting and receiving antennas under M-ary quadrature amplitude modulation (QAM) techniques with Gray labeling and the optimal flat fading demapper.

3.2 Layer of Neural Demapper

Figure 3 shows the layer of neural demapper. Our proposed system replaced the traditional QAM demapper with the neural network-based QAM demapper. A traditional QAM demapper is presented for 5G wireless communication channels and our system modeled with data-dependent noise on the received symbols. Our developed neural network-based QAM demapper includes the covariance information of the received symbol clusters to capture noise variation across the constellation and any dependency between the in-phase and quadrature components. The demapper is advantageous when a system is dominated by distortion as opposed to thermal noise.

The neural network-based QAM demapper is made of three dense layers and ReLU activation functions as shown in Figure 3. The dense layer receives input from all neurons of its previous layer and it performs a matrix-vector multiplication operation. The first two dense layer uses ReLU activation function and the last dense layer uses linear activation function. The ReLU activation function output the input directly for positive value and set zero for negative value. A linear activation function is simply a straight-line function which output weighted sum of neurons.The neural network processed the input as a three dimensional vector

$$[\Re(z), \Im(y), \log_{10}(N_0)]$$

Where $\Re(z)$ and $\Im(y)$refer to the real and imaginary component respectively.

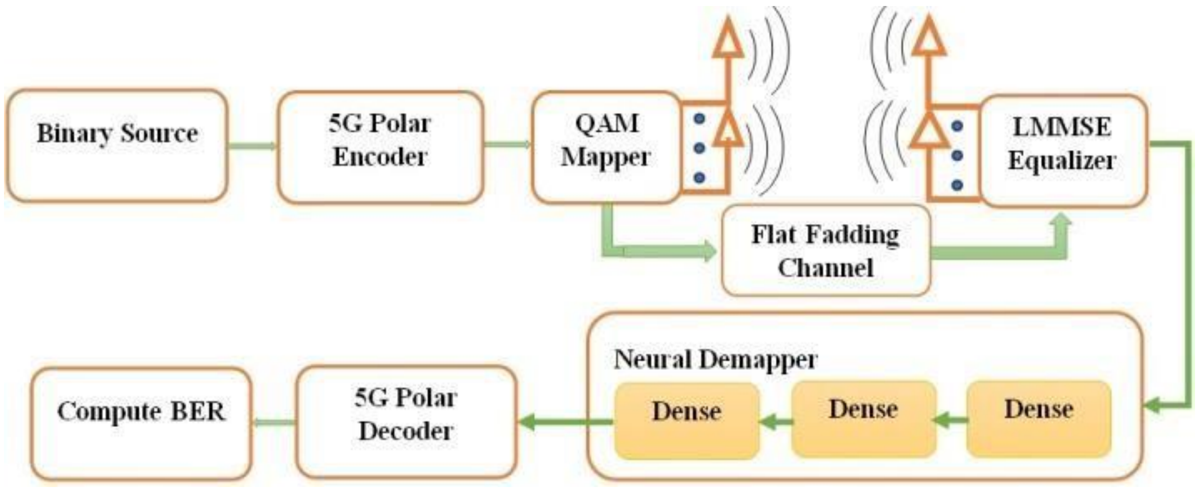

Figure 2 Neural demapper based Polar coded 5G MIMO communication system.

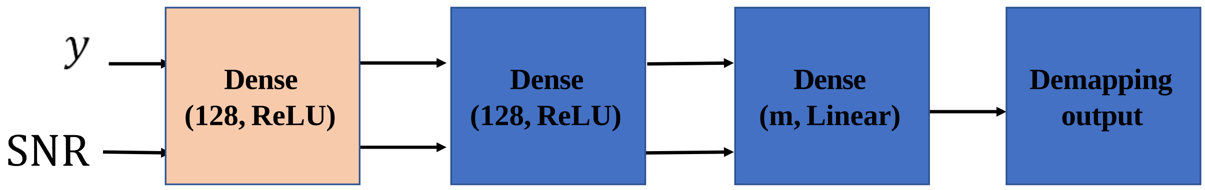

Figure 3 Layers of neural demapper.

The output of the neural network-based demapper consists of LLRs on the bits per symbol mapped to a constellation point. Therefore, the last layer consists of bits per symbol units. Figure 3 shows the layers of our proposed neural demapper model. The training parameters of neural network based demapper are shown in Table 1:

Table 1 Training specification of the proposed neural demapper.

Training Parameters	Value
Batch size	64
Epochs	30000
Optimizer	SGD
Loss function	Binary cross entropy
Modulation	4-QAM, 16-QAM, 256-QAM
Channel	Flat Fadding

4. Results and Discussion

This section analysis the performance of the proposed polar-coded 5G MIMO neural demapper-based communication system with antenna variation under various QAM modulation orders. Throughout this section, the performance investigation criteria are based on bit error rate (BER) versus signal-to-noise ratio (SNR) where x-axis indicates SNR in dB and y-axis indicates

BER. Here, the simulation was performed under flat fadding channel with wide range of SNR from -5 dB to 25 dB. Figure 4 shows the flat fading channel received symbol output with changing the order of QAM modulation.

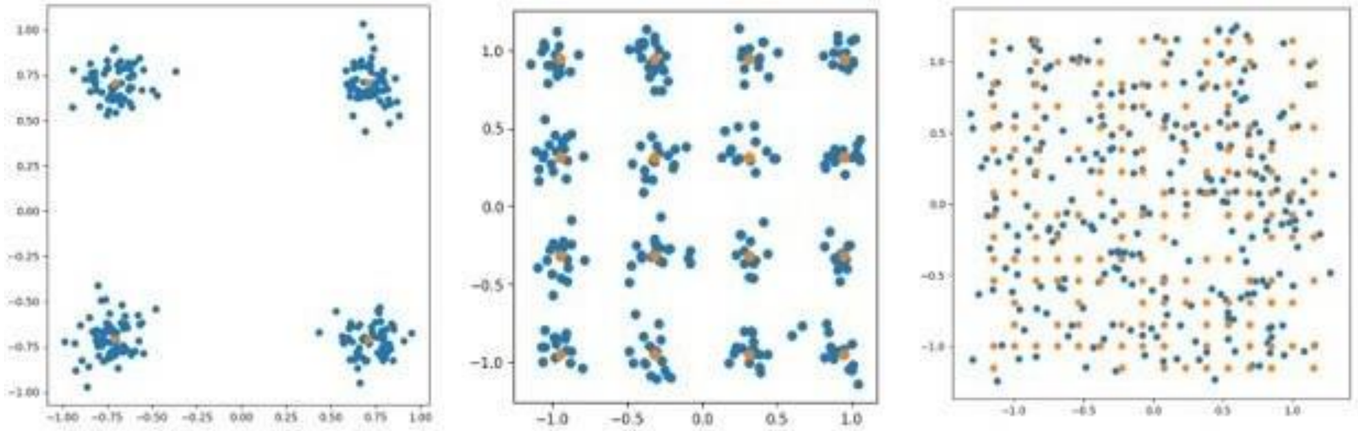

Figure 4 Constellation diagram of 4-QAM, 16-QAM and 256-QAM flat fadding channel received symbol output.

Figure 5 to Figure 7 shows the spectra obtained from the simulation result of the proposed polar-coded 5G MIMO neural demapper-based communication system under different orders of QAM modulation (4-QAM, 16-QAM, 256-QAM) techniques. For performance investigation of the proposed system, we consider a MIMO communication system with 2×3, 2×4, 4×6 and 4×16 transmitting and receiving antennas. As can be observed from the spectra of Figure 5 to Figure 7, the solid blue curve indicates the simulation result of the proposed system with 2×3 transmitting and receiving antennas. Similarly, the orange, yellow, and dark purple of Figure 5 to Figure 7 indicates the simulation result of the proposed system with 2×4, 4×6, and 4×16 transmitting and receiving antennas, respectively.

Figure 5 represents the simulation result for 4-QAM modulated MIMO communication system with 2×3, 2×4, 4×6 and 4×16 transmitting and receiving antennas. It is evident from this figure that over -1 dB, 2×3, 2×4, and 4×6 transmitting and receiving antenna performance gain can be achieved. However, for 4×16 transmitting and receiving antennas, the performance gain can be achieved from -5 dB. Hence, the proposed system performs better with increasing transmitting and receiving antennas.

Similarly, Figure 6 and Figure 7 shows the simulation result for 16-QAM and 256-QAM modulated MIMO communication system, respectively. It is observed from both figures that the performance gain for 2×3, 2×4, and 4×6 transmitting and receiving antenna is over 0 dB and 5 dB, respectively. Furthermore, the 4×16 transmitting and receiving antenna of Figure 6 and Figure 7 achieved performance gains over -2 dB and 3 dB, respectively. Therefore, it can be concluded from the simulation result that the performance of the proposed system is more degraded for higher-order modulation.

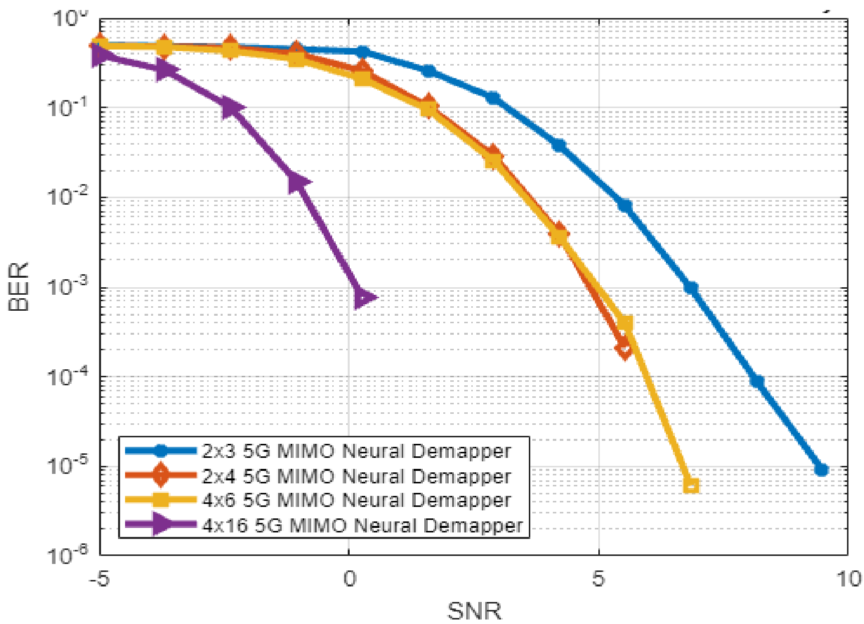

Figure 5 BER Performance of Polar Coded 5G MIMO Communication System under 4-QAM Modulation.

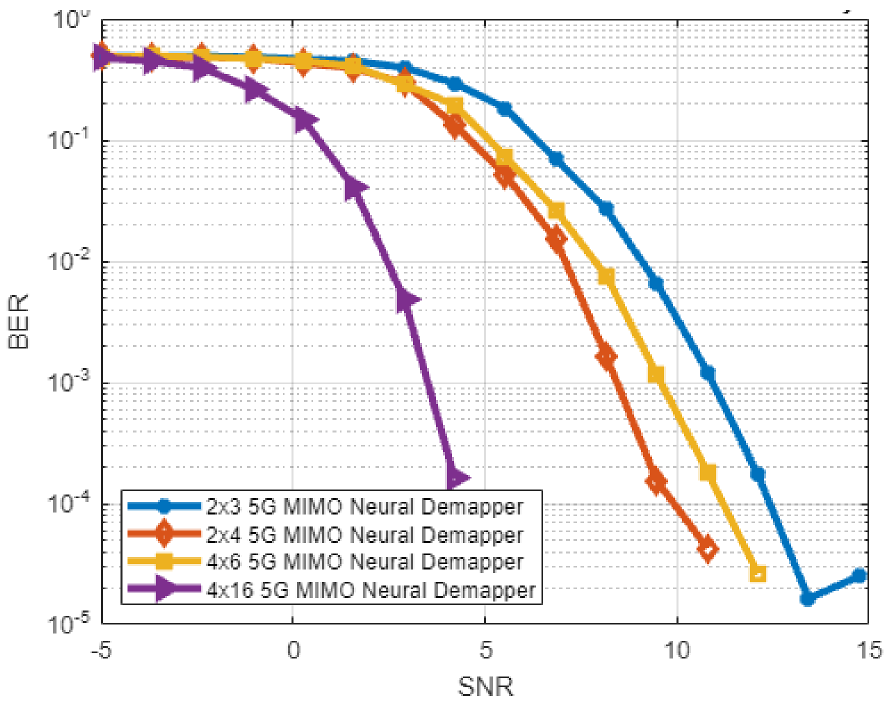

Figure 6 BER Performance of Polar Coded 5G MIMO Communication System under 16-QAM Modulation.

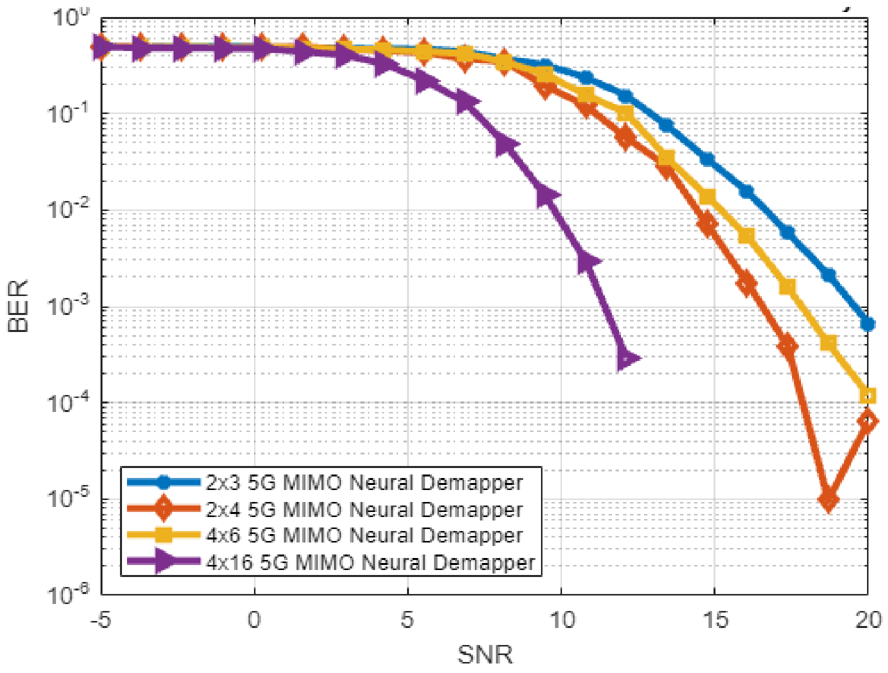

Figure 7 BER Performance of Polar Coded 5G MIMO Communication System under 256-QAM Modulation.

5. Conclusions

We have described and numerically validated the polar-coded neural network-based 5G MIMO communication system. The proposed model is evaluated by varying the number of transmitting and receiving antenna under M-ary QAM modulation. The key novelty is representing the neural network-based QAM demapper instead of traditional QAM demapper. It is noticeable from the simulated result that our proposed system performs better with a lower-order modulation technique. It is also observed that the number of transmitting and receiving antenna has a good impact on system performance. The performance improvements over classic QAM baselines result from geometric constellation shaping and learning the optimal demapper. The proposed system was shown to be capable of significant adverse effects of antenna variation of MIMO communication systems.

Ethical considerations

Not applicable.

Conflict of Interest

The authors declare that they have no conflict of interest.

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