A Deep Learning Approach to 5G Physical Layer Abstraction for Data Channels

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Abstract

The physical layer of fifth-generation (5G) technology is characterized by significant complexity, particularly in its high-consuming computation times during simulations. In this study, we propose a novel abstraction framework for the physical layer of 5G networks to reduce computation times while maintaining high accuracy in the results. This solution is grounded in a Deep Neural Network (DNN) capable of predicting the Block Error Rate (BLER) based on the instantaneous channel state, modulation, and coding rate used in the transmission. The paper details the structure of the framework, the architecture of the employed DNN, and presents results demonstrating the performance of the framework in comparison to classical abstraction mechanisms.

1 Introduction

The fifth generation (5G) has played a critical role in facilitating the implementation of a broad spectrum of services and applications, distinguished by traffic characteristics that significantly differ from those observed in previous networks. As 5G continues to evolve, it not only addresses the escalating demands of existing applications but also unlocks new, unprecedented possibilities, further shaping the dynamic contours of the digital landscape.

In 5G, three use cases can be identified based on the utilization of network resources: enhanced mobile broadband (eMBB), massive machine-type communication (mMTC), and ultra-reliable and low latency communications (URLCC) [1]. The diverse needs of these groups have led to the emergence of new and complex techniques aimed at improving both network capacity and fulfilling user requirements.

These techniques need to be evaluated and compared in accurate simulators before implementation to predict their performance. Therefore, simulators have become indispensable tools for the design, management, and enhancement of a 5G network, continually increasing in complexity as mobile networks evolve.

Thus, the problem considered here is the abstraction of the physical layer in order to reduce the computation time consumed in simulations with the same accuracy as a complete transmission through the physical layer. The importance of the proposal relies on the need for efficient simulators that allow obtaining accurate performance predictions to identify trends and optimize system-level parameters.

Artificial Intelligence (AI) technologies have experienced substantial growth in the field of 5G communications, owing to their capacity to efficiently process large amounts of data [2]. In particular, deep neural networks (DNN) have had a significant impact on the 5G physical layer in different applications (e.g. channel generation or channel state information (CSI) compression) [3].

In this paper, we propose a physical layer abstraction framework based on the use of DNN to reduce simulation times without degrading its accuracy in estimating the BLER as a key performance indicator (KPI). We demonstrate that this abstraction framework accurately predicts the BLER in various scenarios, encompassing straightforward configurations like Single-Input Single-Output (SISO) transmission, as well as in Multiple-Input Multiple-Output (MIMO) scenarios characterized by an escalating number of transmit and receive antennas, resulting in heightened system complexity. The objective is to address the weaknesses of classical algorithms through the application of AI-based techniques.

2 System Model

We are considering a system model based on link-level communication, where the transmission of the Physical Downlink Shared Channel (PDSCH) occurs between the Base Station (BS) and a User Equipment (UE) in the downlink. Figure 1 illustrates the block diagram of the complete system model of a conventional 5G transmission simulator, utilized for dataset generation. To initiate a transmission, the selection of modulation and coding rate is essential. Subsequently, after mapping in the time-frequency resources and employing Orthogonal Frequency Division Multiplexing (OFDM) modulation, the signal needs to traverse the channel. Finally, the UE must receive and demod-

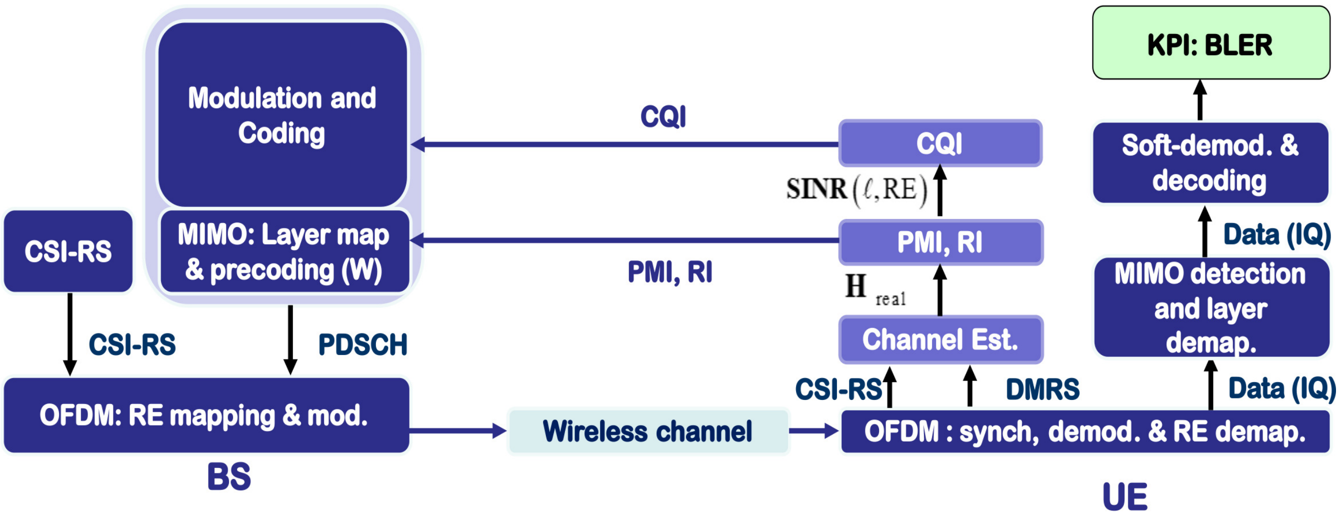

Figure 1. Block diagram of a system model used to generate the dataset.

ulate the signal, estimate the channel for the CSI report, and decode the received data to verify the correctness of the transmission.

To generate the dataset, we simulate complete data transmissions across various channel states to derive the Signal-to-Noise Ratio (SNR) per Resource Block (RB) for each channel. Furthermore, we calculate the BLER for every transmission time interval (TTI), which serves as the label for the supervised training of DNN.

Figure 2 shows the block diagram of the system, focusing on abstracting the physical layer. Notably, in this diagram, there is no need to simulate actual data transmission. Instead, the emphasis is on generating the channel and acquiring the SNR per RB needed as input for the neural network through channel estimation. This input is then introduced into a pre-trained network associated with the Channel Quality Indicator (CQI) selected to execute the transmission. Subsequently, it yields the BLER conditioned to a specific channel state, modulation, and coding rate. This probability can be utilized, through a Bernoulli distribution, to generate the ACK or NACK for the transmission.

The proposed DNN used for BLER predictions is depicted in Figure 3. The input shape of the first layer is $L \cdot N_{RB}$, where L represents the number of layers used in the transmission, and N_{RB} is the fixed number RBs transmitted. The neural network comprises three fully connected hidden layers with Rectified Linear Unit (ReLU) activation functions, as indicated in the figure. Finally, the output layer consists of a single output without an activation function, following the typical structure of neural networks employed for linear regression [4].

The size of the different hidden layers and learning rate has been optimized using hyperparameter tuning, so that the network has been designed according to its complexity.

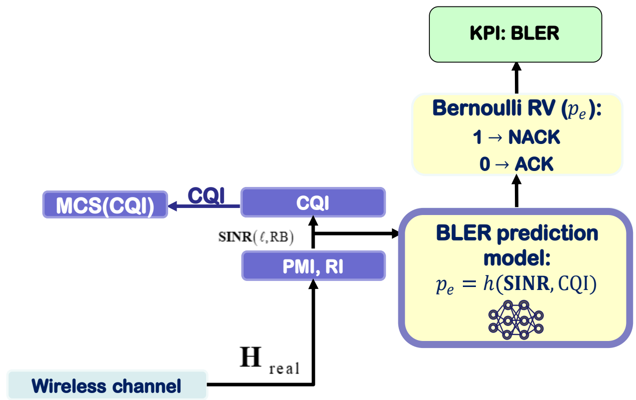

Figure 2. Block diagram of the system model when abstracting the physical layer using DNN.

3 Simulation Results

The simulations presented in this section utilized the parameters specified in Table 1. The training dataset was generated with MATLAB, implementing complete 5G transmissions through MATLAB's 5G Toolbox [5]. The DNN was designed and trained in Python using Tensorflow and Keras, and subsequently exported to MATLAB for comparison. Additionally, the dataset was partitioned into 80% for training, 10% for validation, and 10% for testing.

Figures 4 and 5 display the results obtained for CQI 3, CQI 7, and CQI 12 in both a SISO scenario and a 4x4 MIMO scenario. It is noteworthy that each CQI is characterized by a distinct coding rate and modulation scheme, as outlined in Table 2. These figures demonstrate the effectiveness of BLER prediction in both SISO and MIMO scenarios.

In the legend, the term BLER refers to the block error rate obtained with a complete transmission without physical abstraction. The term BLER EESM refers to the block error rate obtained by abstracting the physical layer through the

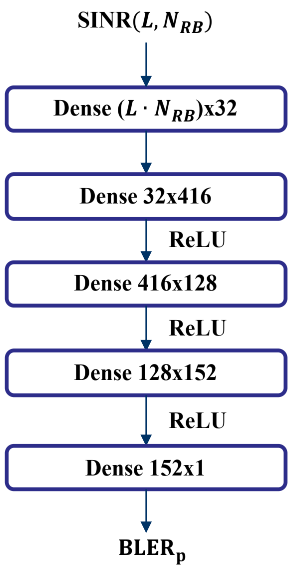

Figure 3. Block Diagram of proposed DNN.

Table 1. Simulation parameters

Parameter	Value
Number of transmitting antennas	[1,4]
Number of antennas in reception	[1,4]
Multipath channel [6]	TDL-A
Delay spread of the channel	300 ns
Doppler shift of the channel	5 Hz
Number of slots simulated (N)	2000
Number of layers used in transmission (L)	[1,4]
Number of RB per transmission (N_{RB})	52
Learning-rate	1e-3

classical Exponential Effective SNR Mapping (EESM) algorithm [8]. Finally, the term BLER DNN represents the block error rate obtained by abstracting the physical layer using the designed neural network.

Figure 4 illustrates how the BLER obtained with the neural network aligns and corresponds with the BLER achievable through abstraction using the EESM, as well as the BLER achievable through a full transmission, all within a SISO scenario.

Figure 5, in contrast to Figure 4, illustrates the prediction accuracy of the DNN in a MIMO scenario. In this simulation, we employ four antennas in both transmission and reception, with the number of layers in transmission set to four. The channel configuration remains consistent with the SISO scenario, as detailed in Table 1. It is evident that the neural network aligns closely with both the classical abstraction method and the full simulation.

Table 2. Modulation and coding rate for different CQIs [7]

CQI	modulation	code rate
3	QPSK	193/1024
7	16QAM	378/1024
12	64QAM	666/1024

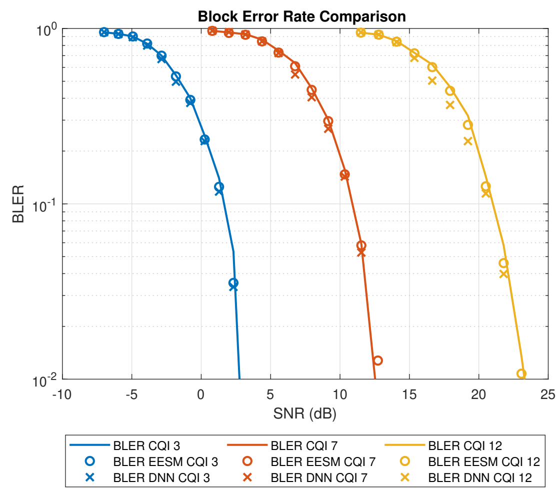

Figure 4. Comparison of the BLER of the complete system versus the abstraction framework of the physical layer by EESM and by DNN in a SISO scenario.

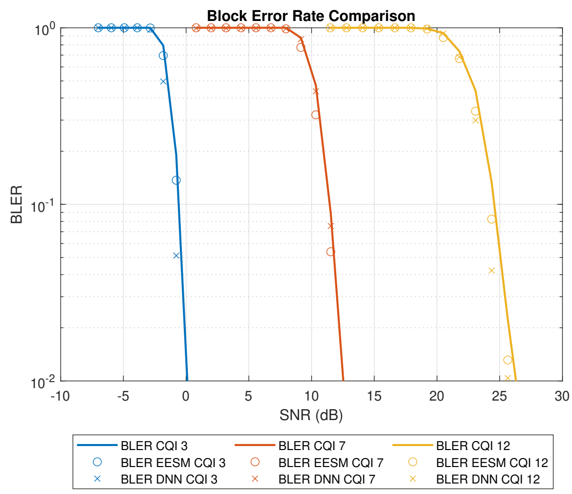

Figure 5. Comparison of the BLER of the complete system versus the abstraction framework of the physical layer by EESM and by DNN in a 4x4 MIMO scenario.

4 Conclusions

In this work, we propose an efficient framework for abstracting the 5G physical layer of data channels, substantially reducing the computational and energy costs of simulations. This abstraction proves valuable for expediting simulations within complex system simulators, especially in scenarios where the base station communicates with each individual user in the cell. Moreover, employing BLER predictions enables early ACK for Hybrid Automatic Repeat Request (HARQ) feedback, contributing to URLLC [9].

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