A Polynomial Neural Network Approach for the Outdated CQI Feedback Problem in 5G Networks

Peterson Yoshioka, José dos Santos, Marcos Falcão, Andson Balieiro, Elton Alves, and Siba Narayan Swain. .

***Abstract*— Accurately reporting a Channel Quality Indicator (CQI) value that denotes the current channel condition is fundamental for 5G networks. However, the time elapsed between the channel condition measurement and its effective use by the base station may render the CQI obsolete, negatively affecting the user equipment (UE) communication. This paper proposes a Polynomial Neural Network solution that considers the Signal-to-Interference plus Noise Ratio (SINR) and user context to estimate the updated SINR for translation into a CQI value. It is based on a self-organizing algorithm (the Group Method of Data Handling - GMDH) that combines the concepts of black-box modeling, connectionism, and induction for computer-based mathematical modeling of multi-variable systems and automatically optimizes its structure with minimal analyst intervention. The results show that our solution presents a high level of accuracy and performance similar to the ideal one, with an absolute difference of only 0.001 in both throughput and spectral efficiency metrics, demonstrating its feasibility to address the outdated CQI feedback problem.**

***Keywords*— Outdated CQI Feedback Problem, 5G Networks, GMDH, Polynomial Neural Network**

I. Introduction

The Fifth Generation (5G) of Wireless Communications is being employed to support a variety of services, including autonomous vehicles, ultra-high definition video streaming, and the Internet of Things (IoT) and provide high throughput (e.g. dozen of Gbps), ultra-low latency (e.g. order of few milliseconds), high reliability (e.g. order of 99.99999%), low energy consumption, and high connection density [1]. Nevertheless, challenges arise in maintaining a high quality of service during wireless communications due to events such as signal reflection, diffraction, user mobility, and interference from other sources.

To address this issue, 5G base stations (gNodeB) employ the Adaptive and Modulation Coding (AMC) technique. It adjusts the modulation and coding schemes (MCS) used for transmission based on the channel quality indicator (CQI) reported by the UE. The CQI aims to reflect the downlink channel condition and assist the gNodeB in making decision regarding MCS and radio resources for communication. Thus, it indirectly affects the achieved throughput, block error rate (BLER), and spectral efficiency. Therefore, accurately reporting a CQI value that denotes the current channel condition is of paramount importance for 5G network link adaptation. However, the time elapsed between the channel condition measurement and its effective use by the gNodeB, which involves tasks such as CQI computation and transmission, may render the CQI obsolete, not reflecting the current channel quality [2][3] and possibly degrading the UE communication (e.g. throughput reduction).

Solutions addressing the outdated CQI feedback problem have been proposed in the literature [2] [3] [4] [5], which are based on CQI or Signal-to-Noise Ratio (SNR) prediction via techniques such as linear extrapolation [5], Long Short Term Memory (LSTM) Neural Networks [3] [4], or linear estimation with stochastic approximation [2]. However, these approaches often overlook the impact of user context, such as position and distance to the Base Station (BS), on the perceived channel condition. They typically consider CQI or SNR for estimating future values, and some are implemented at the gNodeB side [3] [4], potentially overloading it, especially in scenarios with high user density.

In contrast, our paper proposes a Group Method of Data Handling (GMDH) solution that considers not only the CQI or SINR but also user context, incorporating factors like position and distance to the base station to estimate the updated SINR for translation into a CQI value. GMDH is a self-organizing algorithm that combines the concepts of black-box modeling, connectionism, and induction for computer-based mathematical modeling of multi-variable systems [6]. It is a Polynomial Neural Network that automatically optimizes its structure with minimal analyst intervention. We evaluated our solution by using data from 5G simulator [7] in terms of prediction accuracy, spectral efficiency, and throughput, comparing it to an ideal SINR predictor, i.e., one with perfect prediction, zero error. The results show that our solution demonstrates a high level of accuracy and performance similar to an ideal one. There is only a minimal absolute difference of 0.001 in both throughput and spectral efficiency metrics, highlighting its feasibility to deal with the outdated CQI feedback problem. The remainder of this paper is organized as follows. Section II discusses some works. The outdated CQI feedback problem and the proposed GMDH-based solution proposed is presented in Section III. Results and Analysis are conducted in Section IV. Section V concludes this work.

José dos Santos, Marcos Falcão, Peterson Yoshioka, Andson Balieiro, Centro de Informática (CIn), Universidade Federal de Pernambuco (UFPE), Brasil, e-mail: {jrds, mrmf, pmsy, amb4}@cin.ufpe.br; Elton Alves, Universidade do Sul e Sudeste do Pará, Marabá, Brasil, e-mail: elton-alves@unifesspa.edu.br; Siba Narayan Swain, Indian Institute of Technology Dharwad, e-mail:sibaswain@iitdh.ac.in

II. Related Work

Solutions based on prediction have been proposed for the oudated CQI feedback problem in the literature. For instance, in [2], the authors analyze different techniques such as Linear, Linear with Stochastic Approximation (LSA), Kalman Filters, and Discrete Cosine Transform (DCT) Sequences to predict the CQI, with LSA outperforming the others in terms of the complexity-performance tradeoff. In [5], the authors use previous signal-to-noise ratio (SNR) values and linear extrapolation to predict future SNR. However, the proposal does not work properly in scenario with moderate or high speed users.

On the other hand, in [4], a Long Short Term Memory (LSTM) Neural Network proposed to predict the CQI and online retraining is employed to achieve high accuracy even in dynamic scenarios. For predicting CQI, [3] proposes a deep recurrent neural networks (DRNNs) approach based on the time-series of previous CQI values. The authors emphasize that the solution is designed for Unmanned Aerial Vehicle (UAV) control information based on Ultra-reliable and Low Latency communication (URLLC), but do not consider the device context aspects such as device position to estimate the future CQI. These three approaches ([3], [4], and [5]) are single-type input forecasters, but differ in terms of the prediction technique. [3] employs Long Short Term With Memory (LSTM) and Gated Recurrent Unit (GRU) layer. Furthermore, [3] and [4] predict the CQI and operate at the base station, while [5] focuses on the SNR and it is embedded into the user device.

In our previous paper [8], we tackled the outdated CQI feedback problem by proposing a Multi-Layer Perceptron (MLP) Neural solution. The solution considers the UE mobility context (e.g. position, velocity, and movement direction), delay length, and the SINR to predict the updated SINR. In contrast, in the present paper, we adopts GMDH for predicting the updated SINR, mapping it into a CQI value. The selection of inputs for GMDH is guided by Pearson's and Spearman's coefficients to avoid unnecessary overhead or complexity. Unlike the MLP, which requires significant information about the neural network topology (e.g., number of hidden layers, neurons, and their activation function), subjectively defined by the analyst or determined through testing as in [8], the GMDH automatically optimizes its structure. Additionally, beyond evaluating the accuracy of the GMDH solution, we consider its impact on spectral efficiency and throughput, comparing it to an ideal predictor, which has zero error.

III. Proposal

A. The Channel Quality Indicator (CQI)

The channel quality in 5G networks varies across cells due to factors such as position (proximity to the antenna), interference from other sources, signal reflection and diffraction, and user mobility. To respond to these changes and provide the best possible communication service to users, 5G base stations employ link adaptation (LA), where modulation and coding schemes (MCS) and the amount of resources are adjusted based on the channel quality [4]. For instance, in channels with good quality, higher-order MCS may be applied to achieve higher throughput and spectral efficiency. On the other hand, lower-order MCS are most suitable for handling poor channels and avoiding frequent retransmissions.

The channel condition is reported by the UE to the gNodeB in a Channel State Information (CSI) report, which comprises three main components, a Channel Quality Indicator (CQI), Precoding Matrix Index (PMI), and Rank Indicator (RI). Among these, the CQI holds particular significance for link adaptation as it indirectly defines UE communication performance, influencing factors such as data rate and error block rate. The UE determines the CQI based on the reference signal received from the gNodeB, with values ranging from 0 to 15. A higher score indicates better channel quality. Based on the CQI, the gNode selects the best modulation and coding schemes along with determining the amount of resources for transmission in order to maximize the spectral efficiency, while targeting a certain block error rate (BLER)[9], for example.

In this respect, it is crucial that the CQI accurately reflects the current channel quality for a proper LA. However, the delay incurred by tasks performed between the reference signal reception at the UE and the MCS selection by the gNodeB may render the CQI obsolete or outdated. For instance, upon receiving the reference signal, the UE dedicates time to process measurements (e.g. computing the SINR) and translate them into a CQI value. Subsequently, the UE sends the CQI to the gNodeB, introducing delays associated with UL transmission scheduling, transmission itself, and signal propagation. Once the CQI reaches the gNodeB, the MCS selection adds an additional delay to this sequence of events[3]. These cumulative overheads contribute may make the CQI obsolete.

B. The Group Method of Data Handling (GMHD)

The group method of data handling (GMDH) was first introduced by Ivakhnenko for detecting nonlinear systems [6]. It is a self-organizing algorithm that combines the black-box, connectionism and induction concepts for the computer-based mathematical modeling of multi-variable systems via Polynomial Neural Networks. In this way, it automatically sets its parameters and optimizes its structure with minimal analyst intervention [10] Figure 1 illustrates the basic multilayer GMDH structure with n inputs and one output, organized into three parts: input, which comprises input neurons, one for each input variable; intermediate, with layers of neurons, in which neurons of a layer receive inputs of selected neurons from the previous layer; and the output layer.

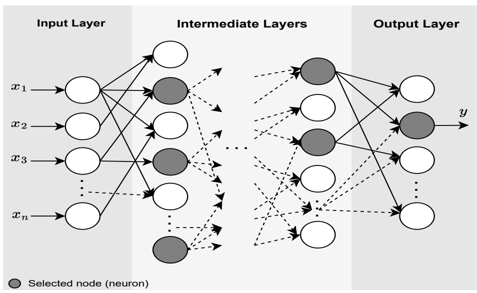

Fig. 1: The basic multilayer GMDH structure

Let $X = x_{1i}, x_{2i}, x_{3i}, \ldots, x_{ni}$ be the input vector composed of n variables and $y_i = f(x_{1i}, x_{2i}, x_{3i}, \ldots, x_{ni})$ its respective desired mapping value for the sample i of a dataset with M observations for each variable, i.e, $i = 1, 2, 3, ...M$. The GMDH is trained to predict the desired outputs, offering estimations $y_i^* = f^*(x_{1i}, x_{2i}, x_{3i}, \ldots, x_{ni})$, where it aims minimizing the difference between y_i and y_i^* for all i, as shown in Eq.1.

$$Minimize \sum_{i=0} M(y_i - y_i^*)^2 \quad (1)$$

In the Ivakhnenko model [6], each neuron output is obtained via second order polynomial functions with two inputs (z_s, z_t), as shown in Eq. 2. The least-squares method (LSM) is employed to adjust their coefficients and thus minimizing the mean squared error (MSE) between the output neuron and the desired one. To prevent overfitting, GMDH randomly selects a percentage (e.g., 70%) of the total data for training, leaving the remaining data for validation, in which the former is used to adjust the coefficients. Moreover, the neurons of each layer undergo a selection process to determine which ones will be considered in the next layer, eliminating weaker combinations in favor of stronger ones. The selection may be done by comparing the fitting errors in the validation stage for each neuron with a threshold (penalty parameter)[10]. Applying this process across the layers, GMDH automatically defines the neurons will compose the final model, creating a complex model by combining simple structures.

$$a_0 + a_1 z_s + a_2 z_t + a_3 z_s z_t + a_4 z_s^2 + a_5 z_t^2 \quad (2)$$

C. Data and Input Variables

To train the GMDH model and estimate the updated SINR, mapping it into a CQI value, we adopted data generated via mmWave simulator [7]. Simulations were conducted with eight different UE initial positions, spanning values for x, y, and z coordinates from 20 to 100. Each simulation lasted 30 seconds, resulting in a total of 23,975 collected samples. Throughout the simulation, we collected data on the UE's velocity, position (x, y, and z coordinates), angle, distance to the closest base station, movement direction, and SINR (in dB). These variables were considered as possible inputs for estimating the SINR at instant $t + \tau$, where τ denotes the delay length (feedback delay) and t the current time. This work defined τ as the time elapsed between two consecutive collected samples, but it also allows for consideration of other values.

To select the proper input variables for the GMDH model, we computed the Pearson and Spearman correlation coefficients. These coefficients evaluate the influence of each input variable at instant t on the SINR at instant $t + \tau$ (target output) and are presented in Table I. The criterion for selection was set as having both correlation coefficients higher than 0.5 (absolute value), resulting in choosing the UE position (x,y,z), distance between UE and the BS, and SINR as input variables.

TABLE I: Pearson and Spearman correlation coefficients

Input Variable	Pearson	Spearman	Selected Variable
SINR	0.97	0.96	✓
Velocity	0.01	0.01	-
Angle (μ)	- 0.16	- 0.16	-
Direction(v)	0.04	0.004	-
Position (x,y,z)	- 0.61	- 0,585	✓
Distance to BS	- 0.90	- 0.92	✓

The first two variables can be obtained through the Global Positioning System (GPS), commonly embedded in current mobile devices, or by using alternative methods such as databases of geo-tagged Wi-Fi hotspots, sensor-based technologies (e.g., cameras), Wifi signal-based localization, Indoor Positioning Services (IPS), as well as their combination [11].The current SINR may be measured by the UE based on the reference signal received from the gNodeB. It is worth noticing that the SINR is commom factor used to derive the CQI to be reported, but other factors can also be considered in this CQI mapping, such as those used in [12].

D. Analysis Metrics

To evaluate our proposal, we considered Spectral Efficiency and Throughput, along with two accuracy metrics: Mean Squared Error (MSE) and R-Square score.

a) Spectral Efficiency (SE):: Electromagnetic spectrum is a natural and scarce resource that requires an efficient use. Thus, spectral efficiency is a measure used in wireless communications to quantify efficiency of the use of the radio frequency spectrum or bandwidth. It is typically given in bit/s/Hz and defined as the ratio between the data rate and channel bandwidth. It can be obtained via Eq. 3, which considers the linear SINR and the Block Error Rate (BLER).

$$SE = log_2(1 + \frac{SINR}{-ln(5BLER)/1.5}) \quad (3)$$

b) Throughput:: measured in bits per second (bps), throughput denotes the amount of data transmitted in given period of time. It can be computed by considering the slot duration, based on the 5G numerology μ, and the number of bits per slot. The latter is determined by taking into account the downlink channel overhead (OH_{dw}) and the transport block size (TBS), as denoted in Eq. 4. The TBS is defined according to the MCS selected by the BS for use in downlink communication.

$$Th = \frac{bits_{slot}}{slot_{duration}} = \frac{(1 - OH_{dw}) * TBS}{(1/2^{\mu})10^3} \quad (4)$$

To compute the TBS [13], the first step involves determining the number of resource elements (REs) allocated for the physical downlink shared channel (PDSCH) within the slot (N_{RE}) using Eq. 5. It considers the number of REs allocated for PDSCH within a physical resource block (PRB), denoted as N'_{RE}, and the number of PRBs allocated to the UE (n_{PRB}). The expression for N'_{RE} is given by Eq. 6, where N_{SC} represents the number of sub-carriers per PRB (12 in 5G networks), N_{symb} is the number of symbols of the PDSHC allocation within the slot (which may be 12 for extended cyclic prefix or 14 for normal cyclic prefix), N_{DRMS} denoted the amount of REs per PRB for demodulation reference signals (DMRS), and the OH_{PDSCH} is the PDSHC overhead, which can assume 0, 6, 12, or 18. In this work, we set it as 0.

$$N_{RE} = min(156, N'_{RE}) * n_{PRB} \quad (5)$$

$$N'_{RE} = N_{SC} * N_{symb} - N_{DRMS} - OH_{PDSCH} \quad (6)$$

Subsequently, the unquantized intermediate variable (N_{info}) is given by Eq. 7, where R represents the code rate, Q_m denotes the modulation order, and v signifies the number of layers. Following this, N_{info} undergoes analysis to define how the quantized intermediate number of information bits (N'_{info}) should be computed and used to derive the TBS. If it is less than or equal to 3840 then N'_{info} is given by Eq. 8 and Table 5.1.3.2-1 (given in [13]) is referenced to find the closest TBS that is not less than N'_{info}. Otherwise, N'_{info} is gotten via Eq. 9 and the TBS is given by Eq. 10, where C is given by Eq.11.

$$N_{info} = N_{RE} * R * Q_m * v \tag{7}$$

$$N'_{info} = max\left(24, 2^n \left\lfloor \frac{N_{info}}{2^{max(3,\lfloor log_2(N_{info})\rfloor-6)}} \right\rfloor\right) \tag{8}$$

$$N'_{info} = max\left(3840, 2^n * round\left(\frac{N_{info}-24}{2^{(\lfloor log_2(N_{info}-24)\rfloor-5)}}\right)\right) \tag{9}$$

$$TBS = 8 * C \left\lceil \frac{N'_{info}+24}{8C} \right\rceil - 24 \tag{10}$$

$$C = \begin{cases} \left\lceil \frac{N'_{info}+24}{3816} \right\rceil, & R \leq 1/4 \\ \left\lceil \frac{N'_{info}+24}{8424} \right\rceil, & R > 1/4 \ and \ N'_{info} > 8424 \\ 1, & \text{otherwise.} \end{cases} \tag{11}$$

c) Model Accuracy:: we have adopted the Mean Squared Error (MSE) and R-Squared (R^2) metrics to assess the accuracy of the GMDH model and select the best configuration for our approach. The MSE is defined in Eq. 12 and measures the average squared difference between the predicted values ($\hat{y}_i$) and the target ones (y_i). The R^2, given in Eq. 13, denotes the model's ability (in percentage) to explain or predict the relationship between the dependent and independent variables. A higher R^2 value indicates a better fit of the model to the data, demonstrating its ability to explain the dataset.

$$MSE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n} \tag{12}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})} \tag{13}$$

IV. Results

To train and evaluate the GMDH model, the data was organized into two sets, training and test, with each one comprising 70% and 30% of the collected samples (23975), respectively. Since the input variables present different scales, we normalized them between 0 and 1 by using minmax operation. In the next section (IV-A), we present the accuracy results obtained by different GMDH configurations in the training and test stages as well as the criteria adopted to select the best setting to compose our GMDH approach. Section IV-B compares the defined GMDH model to an optimal SINR predictor in terms of throughput and spectral efficiency, where it is considered that the optimal solution predicts all values perfectly, i.e, its MSE is zero. The aim is to show the performance proximity between our solution and the ideal one.

A. Model Configuration and Accuracy

To define the best GMDH configuration to be adopted in our scheme, we conducted several tests, varying different parameters, including the criteria for selecting the best nodes/neurons (BN) and computing the errors of the layers (EC), reference function (RF), and penalty parameter (PP). For neuron selection, we considered the following options: (1) validate, where neurons are compared based on a validation error; (2) bias, where the neurons are compared considering a bias error; (3) validate-bias, adopting a combined criterion of (1) and (2); and (4) bias retraining, where neurons are first compared regarding a bias error and then retrained on the total data set. For the computation of EC, two approaches were evaluated. In the fist, the error layer is defined as the topmost best neuron error (top), while in the second, it is the average of the selected best neurons errors (average). In terms of RF, besides the quadratic function, defined in Eq. 2, the linear (Eq. 14) function and its variation (Eq. 15), and the cubic one, a full third-degree polynomial (Eq. 16), were analyzed. For the PP, six values were tested, raging from 0.001 to 2.0. For all configurations, the maximum number of layers, the minimum bandwidth, and the threshold for training stop (ϵ) were set to 10, 5, and 0.001, respectively. The ϵ is compared to the relative layer training error. Table II summarizes the GMDH parameters and their values.

$$a_0 + a_1 z_s + a_2 z_t \tag{14}$$

$$a_0 + a_1 z_s + a_2 z_t + a_3 z_s z_t \tag{15}$$

$$\begin{split} a_0 + a_1 z_s + a_2 z_t + a_3 z_s z_t + a_4 z_s^2 + a_5 z_t^2 + \\ a_6 z_s^3 + a_7 z_s^2 z_t + a_8 z_s z_t^2 + a_9 z_t^3 \end{split} \tag{16}$$

$$(MSE_{train}, MSE_{valid}) \leq MSE_{ref} \tag{17}$$

$$Minimize \ \ |MSE_{train} - MSE_{valid}| \tag{18}$$

TABLE II: Tested GMDH Parameters

Parameter	Value
Best Nodes (BN)	validate, bias, **validate-bias**, bias retraining
Errors of the Layers (EC)	top, **average**
Reference Function (FF)	**Eqs. 2**, 14, 15, 16
Penalty Parameter (PP)	**0.001**, 0.01, 0.1, 0.5, 1.0, 2.0
Maximum Number of Layers	10
Minimum Bandwidth	5
Stop Criterion for Training (ϵ)	0.001

To select the configuration to compose our GMDH scheme, we adopted the criteria defined in Eqs. 17 and 18, considering a MSE_{ref} equals 0.001, and took into account the configuration with the lowest average MSE and highest R^2. Fig. 2 presents the average MSEs achieved by all configurations in the training and test stages as well as the absolute difference between them in 30 rounds (repetitions). It is noted that the criterion denoted in Eq. 17 was met by all configurations, with the configurations between 96 and 143 presenting the lowest values and the 119 one the smallest absolute difference. Although these configurations have achieved similar results, the 108, 109, 114, 115, and 116 ones presented lower average MSE and higher R^2 score (Fig. 3), being the 114 the best configuration in terms of criterion defined in Eq. 18. Thus, the configuration 114 was selected to compose our scheme and its parameters are highlighted in Table II by using a bold font.

Fig. 4 shows the SINR estimated by the GMDH scheme (selected configuration) in comparison to the target value for one execution. The GMDH often follows the target behavior, denoting that it learned the structure of the dataset and is able to deal with the CQI delay feedback problem. Since the

GMDH presented a low MSE (see Fig. 2) and the estimated SINR is quantized into a CQI value via a process based on SINR intervals, the small difference between the target and GMDH output may not lead a CQI error.

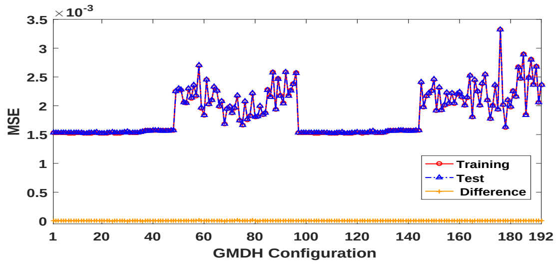

Fig. 2: MSE for Different GMDH Configurations

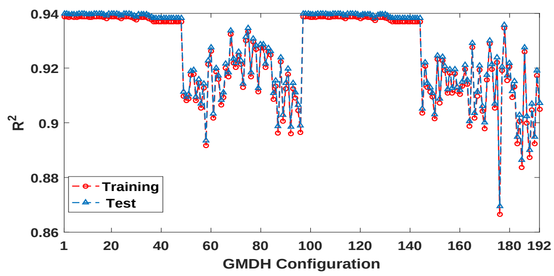

Fig. 3: R^2 score for Different GMDH Configurations

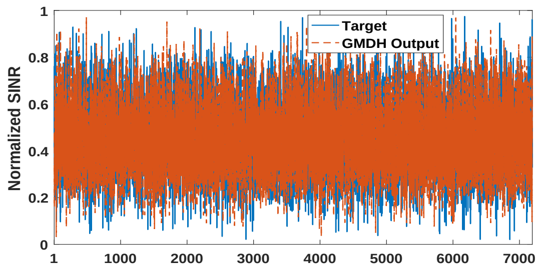

Fig. 4: SINR estimated by GMDH vs target value

B. Throughput and Spectral Efficiency

Fig. 5 presents the results in terms of average spectral efficiency and throughput considering 30 executions and the parameters summarized in Table III. In comparison to the ideal predictor, it is noted that our proposed solution offers similar spectral efficiency and throughput values, presenting an absolute difference of only 0.001 in both metrics, which reinforces the feasibility of our scheme to address the outdated CQI feedback problem in 5G networks.

V. Conclusion

This work proposed a Polynomial Neural Network solution for the outdated CQI feedback problem in 5G Networks. We utilized the Pearson and Spearman coefficients to carefully select the appropriate inputs for feeding into the GMDH, thus avoiding unnecessary overhead. Various spaces of GMDH configurations were considered, allowing the GMDH to automatically optimize its structure and thus selecting the best one. Besides the high level of accuracy, the results showed that our solution exhibited performance similar to the ideal one, with an absolute difference of only 0.001 in both throughput and spectral efficiency metrics, demonstrating its feasibility in addressing the outdated CQI feedback problem. Future works include the design of a hybrid approach, considering different machine learning techniques as reference functions, and exploration of different values for prediction window size.

TABLE III: Parameters for TBS and Throughput Computation

Parameter	Value
Downlink Overhead (OH_{dw})	0.18
Number of Allocated PRBs (n_{PRB})	1
Numerology (μ)	3
Number of Layers (v)	1
Number of Subcarriers (N_{SC})	12
Number of Symbols per slot ($N_s ymb$)	14
PDCH overhead (OH_{PDSCH})	0
N_{DRMS}	0
Target BLER	0.00005

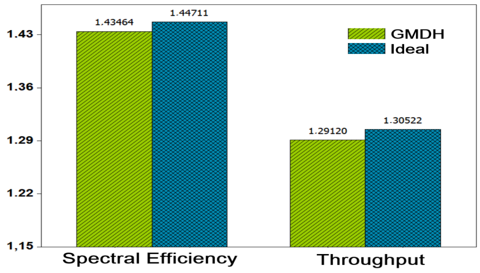

Fig. 5: Spectral Efficiency (bit/s/Hz) and Throughput (Mbps)

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