A Machine Learning Approach for CQI Feedback Delay in 5G and Beyond 5G Networks

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***Abstract*—5G and Beyond 5G Networks apply Adaptive Modulation and Coding to adjust the downlink modulation order and coding rate according to the channel condition, reported by the user equipment. However, the delay incurred in this feedback process may make the channel quality indicator (CQI) outdated and cause severe degradation in the user communication. This paper proposes a machine learning-based approach to deal with the outdated CQI problem. It takes into account the UE context, current signal-to-interference-plus-noise ratio (SINR), and the delay length to compute the updated SINR to be translated into a CQI value. Our proposal acts as a multi-variable function and runs at the UE side, neither requiring any modifications in the signalling between the 5G base station (gNB) and the UE nor overcharging the gNB. Results in terms of mean squared error (MSE) by using 5G network simulation data show its high accuracy and feasibility to be adopted in 5G networks.**

***Index Terms*—CQI Feedback Delay, 5G Networks, Machine Learning**

I. Introduction

The fifth generation of mobile communication (5G) and beyond 5G (B5G) comprise different service categories such as enhanced mobile broadband (eMBB), massive machine-type communication (mMTC) and ultra-reliable and low latency communication (URLLC), which present distinct requirements in terms of latency, connection density, reliability and throughput [1]. Since that the mobile communication experiences unpredictable channel variations due to events such as reflection, diffraction, signal scattering and user mobility, 5G New Radio applies Adaptive Modulation and Coding (AMC) to adjust the downlink modulation order and coding rate and thus achieving high throughput/spectral efficiency, keeping the target block error rate (BLER) under control [2].

The AMC is based on the Channel State Information (CSI) reported by the user, in which the Channel Quality Indicator (CQI) is one of the key parameters. CQI is a 4-bit value [3] that aims at reflecting the current channel conditions. Based on the CSI report, the 5G base station (gNB) schedules radio resources to the user equipment(UE), aiming to provide a certain level of the Quality of Service (QoS), compensate the channel impairments, and reduce multiple re-transmissions. Therefore, CQI plays a key role in the 5G and B5G radio systems.

This work was supported by the Motorola Mobility; the National Council for Scientific (Project No. 433142/2018-9 and Research Productivity Fellowship - Grant No. 312831/2020-0) and Technological Development (CNPq); the Pernambuco Research Foundation (FACEPE).

Inaccurate CQI may result in imbalanced distribution of radio resources among the UEs and unsuitable modulation and coding scheme (MCS), which may degrade the UE performance [4]. For instance, if the a high CQI value is reported, but the real channel condition is poor, the gNB chooses a higher order MCS to be applied in the communication, which leads to a higher block error ratio (BLER) and excessive retransmissions. On the other hand, when a low CQI value is erroneously reported, the data rate and spectral efficiency are impaired because a lower order MCS is selected.

Traditional approaches have adopted the measured signal-to-interference-plus-noise ratio (SINR) of a reference signal sent by gNB to infer the channel quality, translating it into a CQI number [5]. In addition to how the channel condition is estimated, the delay incurred by the CQI feedback process also may lead to an inaccurate CQI, an outdated value, because the channel condition may change between the UE reporting and the feedback reception by the gNB, not reflecting the current channel quality. Moreover, for high mobility users, these changes are more evident and need to be considered in the CQI computation.

In this respect, this paper proposes a machine learning-based approach to deal with the outdated CQI problem, in which a Multilayer Perceptron (MLP) artificial neural network (ANN) takes into account the UE context (velocity, direction and position), current SINR, and the delay length to compute the updated SINR to be translated into a CQI value. Our proposal acts as a multi-variable function and runs at the UE side, neither requiring any modifications in the signalling between gNB and UE nor overcharging the gNB. Its accuracy is evaluated in terms of mean squared error (MSE) by using 5G network simulation data and the results show its feasibility.

This paper is organized as follows. Section II presents works that address issues related to the CQI feedback process. Section III describes the proposed ANN-based scheme for dealing with the outdated CQI problem and presents accuracy results. Section IV concludes this paper and outlines future directions.

II. Related Work

Since the CQI indicator is a key-element used by the gNB to select the most suitable MCS and the amount of radio resources to be used in the gNB-UE link, the value reported by the UE has to reflect the current channel condition. However, the CQI feedback process raises three main issues: (1) the accuracy of the CQI computation/estimation,i.e., how the channel condition is measured and mapped into a CQI value; (2) the CQI feedback delay, which may result in a outdated CQI value due to the changes in the channel condition during the CQI transmission time (from the UE to the gNB); (3) the CQI feedback overhead, an excessive signalling in the uplink that takes place when a short interval between the report is adopted, specially in scenarios with high user density (e.g. crowded events).

Different approaches have been proposed to address these issues. For instance, in [6] the authors deal with the CQI feedback delay by predicting the signal-to-noise ratio (SNR) via linear extrapolation. So, the UE predicts the future SNR based on the previous ones that are selected based on the user speed, with the result being mapped into a CQI value. Although the scheme presents low complexity, it does not work when the user is moving at moderate or high speed. [7] also addresses the feedback delay, but proposes a Long Short Term Memory (LSTM) Neural Network-based CQI prediction scheme with online retraining to achieve high prediction accuracy even in dynamic environments. Both proposals ([6] and [7]) act as time-series forecasters with a single input type, but [7] differs from [6] by predicting the CQI directly and running at the BS.

By addressing the CQI computation accuracy, the authors in [5] claim that factors such as the UE mobility impact on the signal quality as it reflects on the multipath delay spread size, i.e., a larger spread leads to a larger transmission delay and a worse channel quality. Consequently, they propose a CQI scheme that jointly considers SNR and the maximum multipath delay spread of instantaneous channel state to achieve a precise CQI under fading channels. In [8], the authors propose a CQI mapping algorithm that considers the Spectral Efficiency (SE) and Energy Efficiency (EE) tradeoff while keeping the BLER under control and define weights for SE and EE that may reflect the operator priorities or react to the network conditions. In [4] a machine learning (ML)-based framework to predict the SNR considering the UE under different speeds and channel models is presented. Three ML techniques are studied (stochastic gradient descent, multilayer perceptron and support vector machine) that take the SNR and CQI values as inputs. Besides the issue addressed, [8] [4] differ from our proposal as they are designed to run on the BS and do not consider the UE velocity to compute the CQI or SNR, just for selecting the prediction model to be applied in [4].

To reduce the CQI feedback overhead via spatial correlation of wireless channels, [9] [10] propose Gaussian Process Regression-based prediction that selects an appropriate number of CQI reports (SNRs) from some UEs to estimate the CQI for the remaining ones. The estimator accuracy and the user density are used to adjust an offset parameter in [9] and thus improving the prediction. Different from our proposal, [9] [10] are limited to static environments (no moving users) and strongly dependent on the number of users, not working properly in low user density scenarios. In [2], the signaling overhead is reduced by combining subband level report (i.e., the user reports a CQI for a group of resource blocks) and aperiodic feedback (i.e., gNB instructs each UE on when reporting). Moreover, the authors apply Gaussian process regression to predict the CQI and compensate for the CQI feedback reduction, adjusting the prediction window according to the packet loss. The proposal is evaluated in scenarios with moving users, however, the UE speed is not an input to the predictor.

In [11], the authors propose a CQI mechanism for multicast unmanned aerial vehicle (UAV) systems in which the BS determines the suitable MCS for UAVs in the same multicast group based on their CQI feedback. The mechanism provides a fixed CQI channel per group regardless of the amount of UAVs. Although the proposal aims at reducing the overhead signalling, no metric was analyzed to quantify it. Moreover, the authors do not take into account the high mobility of the UAVs, even though it may change the UAV position and channel quality perceived between the CQI feedback and the MCS selection, making the proposal unsuitable for UAV systems. In [12], the CQI feedback overhead is reduced by estimating the CQI of some users via CQI values reported by others. The approach comprises two neural networks (NN) running on the BS: an NN-based binary classifier for selecting the UEs and subbands (SBs) to be used to estimate the CQI; a dense NN estimator for predicting the CQI of non-selected users.

In addition to the main addressed problem, other characteristics (e.g. input types, output, technique and goal) may be pointed to clarify the differences between our work and those previously discussed, as summarized in Table I. For instance, our proposal is designed to run on the UE, not requiring any change in the signalling protocol or gNB. Moreover, it takes multiple input types (e.g. UE position, speed and movement direction, delay time and current SINR) to estimate the updated SINR to be translated into a CQI value. In this respect, the ANN is adopted as a multi-variable function instead of a time-series predictor as the previous approaches usually do.

III. Proposed Scheme and Results

In new radio (NR) system, the CQI is an important scheduling information sent by the user to the gNB to express the current channel condition. It is used by the scheduler at medium access layer to allocate resource blocks (RBs), define the MCS and the Transport Block Size (TBS) to be adopted in the downlink channel, and, thus determining how much data will be transmitted at each time slot [7]. In this respect, to perform a proper resource scheduling to the user, it is imperative that the CQI value accurately expresses the channel quality at time that the gNB makes the decision. However, the delay incurred by the CQI transmission, i.e., the time elapsed between the sending by the user and the reception at the gNB, may make the CQI to be outdated.

TABLE I
APPROACHES FOR CQI FEEDBACK RELATED PROBLEMS.

Paper	Proposal	CQI problem	Technique	Goal(s)	Side	Inputs	Output
[2]	A packet loss and CQI prediction approach that assigns personalized prediction windows to the users.	Feedback overhead	Gaussian Process Regression	To minimize the packet loss and limit the CQI signalling overhead	BS	CQI and packet loss	CQI and packet loss
[4]	A ML-based approach to predict SNR	Innaccuracy	Machine Learning (SVR, MLP, SGD)	To provide a more accurate channel quality estimation	BS	CQI and SNR	SNR
[5]	A multipath delay spread-aware CQI scheme for LTE system	Innaccuracy	Empirical SNR/Delay - CQI mapping based on simulation data	To achieve more precise CQI under fading channels	UE	SNR and Multipath Delay Spread	CQI
[6]	A linear extrapolation-based scheme to predict SNR and map it into a CQI value	Feedback delay	Linear Extrapolation	To improve the network throughput	UE	SNR	SNR and derived CQI
[7]	An LSTM-based CQI prediction method and an online training module in ns-3	Feedback delay	LSTM Artificial Neural Network	To improve the CQI prediction accuracy	BS	CQI	CQI
[8]	A CQI mapping algorithm that considers the Spectral Efficiency x Energy Efficiency tradeoff	Estimation	The VIKOR ranking method and weighted sum	To balance SS and SE in the MCS selection	BS	CQI and weights for EE, SE and coding rate	CQI
[9]	A SNR prediction scheme based on the SNR reported by spatially correlated UEs.	Feedback overhead	Gaussian Process Regression	To reduce the CQI feedback overhead and improve the prediction quality	BS	SNR and spatial correlation of users	SNR and CQI
[10]	A SIR prediction scheme that uses SIR from spatial correlated users	Feedback overhead	Gaussian Process Regression	To reduce the CQI signaling overhead	BS	SIR and spatial correlation from a set of users	SIR
[11]	A CQI feedback scheme for UAV multicast system	Feedback overhead	Minimun functon and fixed channel for CQI feeback per group	To reduce the signalling overhead and increase the spectral efficiency	BS	CQI	CQI
[12]	A CQI report scheme for enhancing the URLLC	Estimation	The worst-case estimation	To accurately estimate and report the the worst-case SINR conditions	UE	SIRN	CQI
[17]	An ANN-based selector and a Dense ANN-based for users/subbands selection and CQI estimation	Feedback overhead	Artificial Neural Networks	To reduce the CQI feedback signalling overhead	BS	CQI of selected subbands/users	CQI
Our Proposal	A ML-based approach with multiple inputs for CQI feedback delay	Feedback delay	MLP Artificial Neural Network	To accurately estimate the SINR considering the cqi feedback delay	UE	UE velocity, movement direction and position, delay length and SINR	SINR

To deal with the CQI delay problem, we design a machine learning-based approach that considers the UE context (e.g. position, velocity and movement direction) and the measured SINR at instant t and the delay length (τ) to compute the updated SINR, i.e, its value at the instant $t+\tau$, which is mapped into a CQI value to be reported by the user. This mapping may be done as usual, by using the CQI table mapping received from the gNB, or adopting schemes such as those proposed in [4] [12] [13]. Our system is flexible enough to admit different mapping ways. Moreover, it runs on the UE, not requiring any change in the signalling protocol or in the BS. Fig. 1 illustrates our proposal.

The UE context may be obtained via position systems such as the Global Positioning System (GPS), which is commonly embedded in the mobile devices, and the SINR is measured based on the reference signal sent by the gNB. For SINR estimation, we adopt a multilayer perceptron (MLP) artificial neural network (ANN) consisting of a 5-neurons input layer, with each one representing an input feature (UE velocity, movement direction and position, SINR or delay length); an 1-neuron output layer, which refers to the updated SINR, i.e., the SINR at the instant $t+\tau$. The number of hidden layers, neurons in the hidden layers as well as the other ANN hyper-parameters (e.g. activation function and learning rate) are described in Section III-A.

A. ANN Topology and Accuracy Results

To define the ANN configuration to be adopted in our scheme, several tests were conducted with different Multilayer Perceptron ANNs [14] varying parameters such as the number of hidden layers (NHL), number of hidden layer neurons (NHLN), activation function of hidden layer neurons (AFHL),

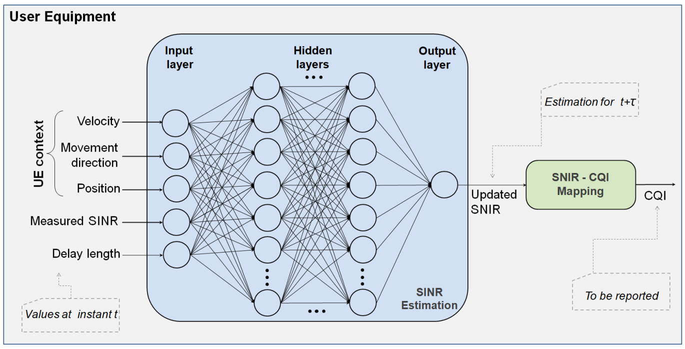

Fig. 1. Proposed scheme

and learning rate (LR). All tested ANNs used five neurons in the input layer (NILN) and one neuron in the output layer (NOLN) with linear activation function (OLAF). The backpropagation learning algorithm [14] was chosen to train the ANNs. Table II summarizes the parameters and analyzed values and indicates that the sigmoid (Eq.1) and hyperbolic tangent (Eq. 2) functions were evaluated as functions for hidden layer neurons.

$$Logisg(x) = \frac{1}{1+e^{-x}} \tag{1}$$

$$Tansig(x) = \frac{2}{1+e^{-2x}} - 1 \tag{2}$$

The number of neurons in the hidden layer strongly influences the ANN learning process and performance. Using too few hidden neurons would result in an ANN that is unable to learn the data structure. On the other hand, so many hidden neurons would dramatically increase the ANN complexity and its learning time, without yielding any significant improvement in the performance [14]. The number of hidden layers also impacts on the ANN's efficiency and time complexity. When the number of hidden layers does not match the problem complexity, the overfitting or underfitting conditions may take place. In the former, the ANN with a large number of hidden layers loses its generalization ability over the data to be tested. In the latter, the problem complexity is underestimated by adopting an ANN with insufficient hidden layers, which produces inefficient results [15]. Thus, six and three different values for the number of hidden neurons and number of hidden layers were analyzed, as shown in Table II.

Additionally, since the learning rate also impacts on the ANN training (e.g. a very low (high) LR can make the learning process too slow (cause large oscillations) [14], three LR values were considered. We combined all the values shown in Table II and analyzed 144 ANN configurations. To choose the ANN to compose our scheme, we adopted the criteria (3) and (4), and took into account the ANN complexity. The MSE_{ref} represents the reference (desired) mean squared error (MSE), the MSE_{train} and MSE_{valid} refer to the MSE achieved by the ANN in the training and validation stages, respectively. These criteria aim at selecting the ANN that not only learns the data characteristics in the training stage but also provides a great generalization capacity when faces new data. In our approach, we considered the MSE_{ref} equals 0.01 (1%).

$$(MSE_{train} \leq MSE_{ref}) \ and \ (MSE_{valid} \leq MSE_{ref}) \tag{3}$$

$$Minimize \ \ |MSE_{train} - MSE_{valid}| \tag{4}$$

TABLE II
TESTED ANN HYPER-PARAMETERS AND VALUES

Hyper-parameters	Values
Number of hidden layers (NHL)	1; 2; 3
Number of hidden layer neurons (NHLN)	5;10;15;20;25;30
Activation function of hidden layer neuron (AFHL)	Tansig; Logsig
Learning rate (LR)	0.01; 0.045; 0.1

The data used to analyze the ANNs were generated by the 5G/mmwave ns-3 simulation framework [16]. A 5G network was simulated with the UE speed, movement direction and position varying during the simulations, leading to different CQI and SINR values. An amount of 2633 samples was collected, being 70% and 30% considered for ANN training and validation, respectively.

Fig. 2 presents the average results for all ANN configurations, obtained by executing 30 times each. Almost all configurations satisfied the criterion 3. The configuration #48 (1 hidden layer with 35 neurons, sigmoid AFHL and LR equals 0.2) achieved the lowest error training (0.003217), but its validation error (0.005) led to a bigger error difference (0.001782) than the configuration #38, which got 0.0004008, 0.004127 and 0.004528 for error difference, training and validation errors, respectively. The best configuration in terms of criterion 4 was the #91, with difference value equals 0.0003183, but at a cost of higher complexity (2 hidden layers with 30 neurons each) and a slight higher training error (0.00474) compared to the configuration #38, which comprises 1 hidden layer with 25 neurons, sigmoid activation function and learning rate equals 0.1. In this respect, we selected the configuration #38 to compose our scheme, which is summarized in Table III.

TABLE III
SELECTED ANN CONFIGURATION

Parameter	Value
Number of input layer neurons(NILN)	5
Number of hidden layers (NHL)	1
Number of hidden layer neurons (NHLN)	25
Activation function of hidden layer neurons	Sigmoid (Eq. 1)
Number of output layer neurons (NOLN)	1
Activation function of output layer neuron	Linear
Learning rate (LR)	0.1

B. Estimated versus Real SINR

Fig. 3 shows the SINR estimated by our scheme in comparison to the real (target) value. In general, our scheme follows the real data behavior, with few peaks that cause mismatch's

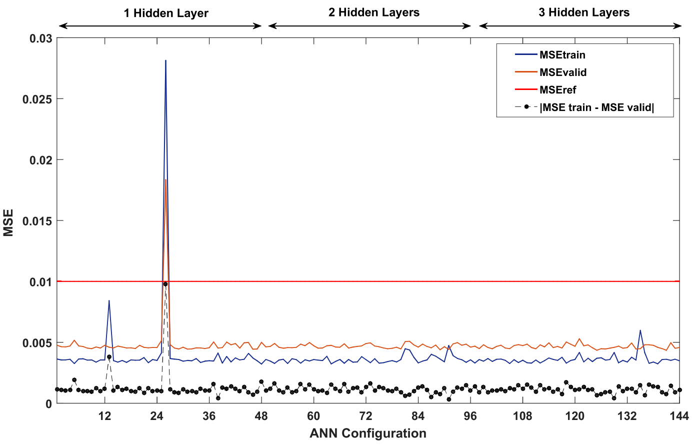

Fig. 2. Results for different ANN configurations.

but without leading to a high MSE (as seen in Fig. 2). It shows the feasibility of our scheme to be adopted to overcome the CQI delay feedback. It is worth mentioning that, as shown in Fig. 1, the estimated SINR is quantized into a CQI value. This process may consider diverse factors such as spectral efficiency and error block rate (BLER) [13], energy efficiency and specral efficieny tradeoff [8] or application requirements [12], and it is not the concern of this paper. Moreover, when the CQI quantization is based on SINR intervals, the difference between the target and ANN values may not lead a CQI error.

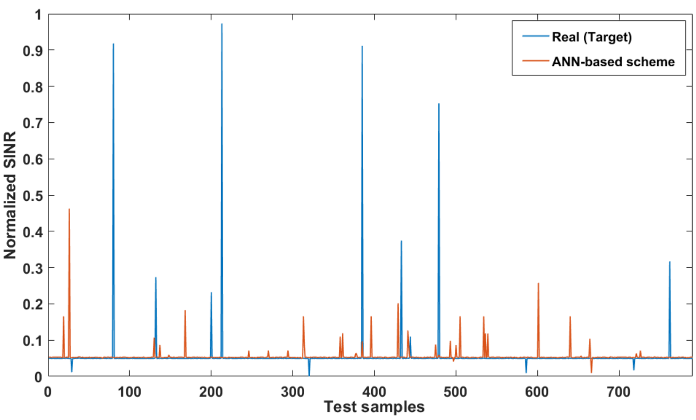

Fig. 3. SINR estimated by the ANN-based Scheme in comparison to the Target value

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IV. Conclusion

This paper proposed a machine learning-based approach to address the CQI feedback delay problem. We considered multiple input variables (UE context, SINR and delay length) to accurately estimate the SINR and run several tests to select the best ANN configuration. The results showed a high accuracy of our scheme, which implies that it may assist a proper MCS selection by the gNB. Although not addressing, our proposal supports online ANN re-training [7] in response to the changes in the wireless channel, where the processing load may be offloaded to the network edge nodes (e.g. multiple access edge computing nodes), not overcharging the UE. Future directions include analyzing the proposed solution when embedded in a simulator or testbed and combine it with different CQI mapping schemes in scenarios with different 5G service types.

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