Logistic regression for BLER prediction in 5G

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***Abstract*—In this work, a block error rate (BLER) predictor for 5G based on logistic regression is presented. The regression is fed with transmission parameters and channel statistics. With these features, the predictor can model the behaviour of the transmission chain, including the low parity channel code (LDPC). In particular, for each modulation and coding scheme (MCS), the regression model uses as features the mean of the SINR over the allocated resources and the squared distance to the mean. Moreover, a single model able to cope with a set of modulation and coding schemes (MCSs) at the expense of certain accuracy loss is also proposed, and its performance evaluated. Possible applications for the regression models such as end-to-end modelling or as part of the adaptive modulation and coding (AMC) function are explored. Results show that the model has excellent accuracy in a wide set of scenarios.**

I. INTRODUCTION

In recent years, the main aspects of 5G have been defined and deployment of the network has begun [1]. One of the most important features of this standard is the distinction between three types of service requirements depending on the use case: enhanced Mobile Broadband (eMBB), massive machine type communications (MMTC) and ultra-reliable low-latency communications (URLLC). Due to the huge differences between their requirements, a fine optimization of the radio access network (RAN) is required. Machine learning (ML) techniques are considered as the way to reach the optimization and one of the main keys for 6G development [2].

A wide set of works can be found in literature which proposes the use of ML in different areas of wireless networks [3]. ML techniques allow not only implementing functionalities but also system modelling. Within the physical and link layer field in 5G, block error rate (BLER) modelling is easily identified as a candidate for ML application [4].

A transport block in 5G [5] is a set of bits jointly coded by a low parity channel code (LDPC) after appending a cyclic redundancy check (CRC). BLER modelling can be described as the estimation of the probability for a transport block to reach the receiver with errors, that is, BLER modelling considers link-level transmission. At that stage, the influence of implementation details are huge, thus evaluating performance has to be done per equipment version. A good BLER model should be accurate while simple enough to allow a user equipment (UE) to carry out the predictor calculation.

This work presents a technique to predict the BLER by logistic regression based on some transmission parameters and channel statistics. This could be useful in several 5G functions such as adaptive modulation and coding (AMC). An analysis of this extremely important technology in 5G serves as test for the instantaneous BLER model. Another utility for BLER prediction is serving to abstract the link-level at a system level design.

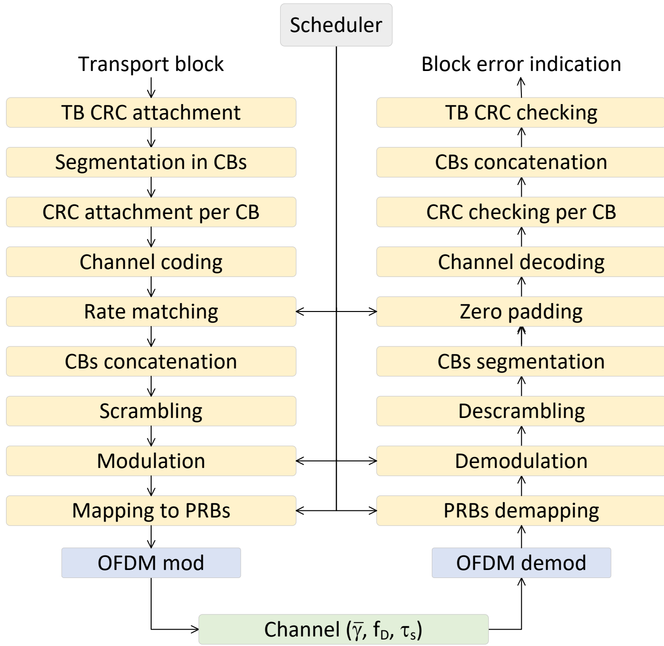


Fig. 1. Transmission chain for a transport block along one slot.

The rest of the paper is organized as follows. First, the system model is presented. Then, two BLER prediction models based on logistic regression are described and the dataset used to train is examined. In Section IV, their performance is evaluated. Finally, some concluding remarks are exposed.

II. SYSTEM MODEL

At 5G, transmission at both downlink and uplink is carried out by modulating QAM symbols via orthogonal frequency division multiplexing (OFDM) [6]. The total number of available subcarriers as well as the subcarrier spacing, Δf, can be adjusted to the specific scenario. Specifically, Δf is given by $15 \cdot 2^{\mu}$ (kHz), being μ the system numerology. One slot is formed by M OFDM symbols and its duration is also variable: as Δf grows, the slot lasts shorter. A simplified transmission chain at each slot is shown in Fig. 1.

The scheduler (out of the scope of this paper) allocates L physical resource blocks (PRBs) to the user during one slot. The transport block is thus transmitted over N resource elements (REs) in the time-frequency grid of one slot, with N evaluated as $M \cdot L$ minus those REs devoted to signalling or reference signals. Moreover, the scheduler assigns the modulation and coding scheme (MCS) to be used, which in turns determines the size of the QAM modulation as well as the coding rate to be employed.

The transport block (TB) in Fig. 1 is formed by transport block size (TBS) bits. The TBS is determined by the number of allocated REs N and the spectral efficiency of the employed MCS[1]. The TB is appended a CRC which is checked at the receiver to detect errors. In 5G, each transport block is segmentated in a set of code blocks (CBs), each with its own CRC in order to allow retransmissions per code block or CB group[2].

The resulting coded bits are used to modulate the QAM symbols and create the OFDM waveform after mapped to the allocated PRBs. At downlink, data from other users might be multiplexed over the same OFDM resource grid, while at uplink zeros are set over those unused PRBs. However, for this work, it is supposed only one user.

In this work, the Tapped Delay Line Channel (TDL) channel model as given in [7] has been considered with delay spread given by τ_s. In this multipath scenario, the received signal after OFDM demodulation can be written as

$$y_n = h_n x_n + \omega_n \tag{1}$$

where x_n is the QAM complex symbol transmitted over the n^{th} RE and ω_n is the Gaussian noise and interference. h_n is the complex channel response for each RE. At the same OFDM symbol, correlation among channel responses at different subcarriers is given by the Fourier transform of the power delay profile (PDP) of the channel [6]. At the same subcarrier, correlation among channel responses at different OFDM symbols depends on the Doppler frequency f_D.

Note that, although OFDM is thought to avoid the interference between symbol and subcarriers, adverse effects of wireless channels such as high Doppler shift or a high time dispersive channel response produce intersymbol interference (ISI) and intercarrier interference (ICI) [6]. Thus, ω_n is not only thermal noise but includes other RE interference. Its power can be measured from the demodulation reference symbols (DRS) as [8]

$$N_{eq} = \frac{1}{N_T} \sum_{n=0}^{N_T-1} |y_n - h_n x_n|^2, \tag{2}$$

with N_T the number of RE over which the averaging has been carried out. By this estimation, and being S the received power of the signal, the signal-to-interference-plus-noise ratio (SINR) for each RE can be calculated as

$$\gamma_n = \frac{S}{N_{eq}} |h_n|^2. \tag{3}$$

III. BLER PREDICTION

In this work, it has been employed the logistic regression to model the BLER. This ML technique is accurate in situations where the output of the estimation is a probability.

Considering the aforementioned transmission model, an associated vector of SINR $[\gamma_1, \gamma_2, \gamma_3, ..., \gamma_N]$ could be assigned to each TB. In order to compress it into a couple of scalars, it is possible to define the average SINR of the TB, γ, and the average squared distance to the mean, σ, which are given by:

[1]We assume single antenna transmission and reception, but the proposed modeling method can be easily extended to multiple input multiple output procedures.

[2]Retransmissions are not taken into consideration in this work.

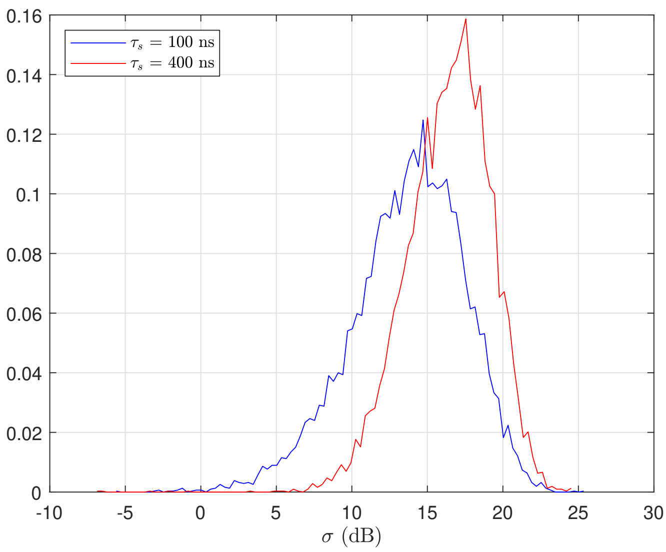


Fig. 2. PDF of σ from a TDL-A channel with f_D = 50 Hz and $S\bar{N}R = 20$ dB

$$\gamma = \frac{1}{N} \sum_{n=1}^{N} \gamma_n; \quad \sigma^2 = \frac{1}{N} \sum_{n=1}^{N} (\gamma_n - \gamma)^2. \tag{4}$$

The construction of the feature vector Ψ based on these statistics allows the full consideration of the channel response. On one hand, γ is the traditional parameter for error rate determination given a channel. Note that γ mean is the average channel SINR, notated by $\bar{\gamma}$ in this work. As more REs are taken, more similar its value will be to $\bar{\gamma}$. On the other hand, σ describes how fast channel changes in the allocated REs. An example of the probability density function (PDF) of this second statistic can be observed in Fig. 2. In this figure, it is shown the incidence of a variation of the delay spread in σ. A longer delay spread implies a minor coherence bandwidth and, hence, faster variations within the TB. The same behaviour is obtained varying the Doppler shift: as it increases, the coherence time is reduced so σ also grows.

In the first model proposed, named as model A, instantaneous BLER for the i^{th} MCS is modeled using as feature vector $\Psi = [1, \gamma, \sigma]$, that is,

$$iBLER_i(\gamma_1, \gamma_2, ..., \gamma_n) \approx B_i(\gamma, \sigma) = \frac{1}{1 + \exp(-\alpha_i^T \Psi)}. \tag{5}$$

The values for $\alpha_i^T = (\alpha_0^{(i)} \ \alpha_1^{(i)} \ \alpha_2^{(i)})$ are to be found to approximate the BLER for a specific MCS used over N resource elements and using a certain subcarrier spacing. One set of coefficient has to be stored in memory per MCS to be predicted.

Another scheme for the logistic regression, referred hereinafter as model B, is presented in order to include the MCS in the feature vector. By taking $\Psi = [1, \gamma, \sigma, i]$, only one set of coefficients $\alpha^T = (\alpha_0 \ \alpha_1 \ \alpha_2 \ \alpha_3)$ has to be stored in memory. As counterpart, generalization in the logistic regression implies certain accuracy loss.

A. Dataset generation and analysis

It is necessary to collect a huge amount of data in order to fit the logistic regression storing γ, σ and an indicator regarding

TABLE I
SIMULATION PARAMETERS FOR DATASET GENERATION

Parameter	Values
Channel Model	TDL-A, TDL-B, TDL-E
Delay spread (τ_s)	100, 200, 400 (ns)
Doppler shift (f_D)	50, 210, 370 (Hz)
Number of allocated RE	504
MCS index	From 0 to 28
Δf	30 kHz

if the TB has been corrupted or not for each transport block. A set of simulations have been carried out varying the Doppler shift and the delay spread. Channel parameters are all the possible combinations from those shown in Table I. Note that also values of τ_s longer than the cyclic prefix has been simulated, producing ISI and ICI. intercarrier interference also appears at high values of f_D.

Once data is prepared, it is opportune to analyze its characteristics before its use to train the logistic regression. As illustrated in Fig. 3, there are two clearly differentiated regions what support the accuracy of γ and σ as descriptors of the channel response. It has been used the logarithm scale so as to improve the fit by limiting the variability of the features, specially γ. Furthermore, for low MCSs, the bound which separates the error/non-error regions is approximately linear, while higher MCSs have a more non-linear behaviour. This causes a better fit for low MCSs.

IV. RESULTS

A. Average BLER modelling

System level simulators are usually too complex to allow detailed link level simulations. The average BLER is easily obtained by time averaging:

$$\bar{B}_i(\bar{\gamma}) = E[B_i(\gamma, \sigma)] \tag{6}$$

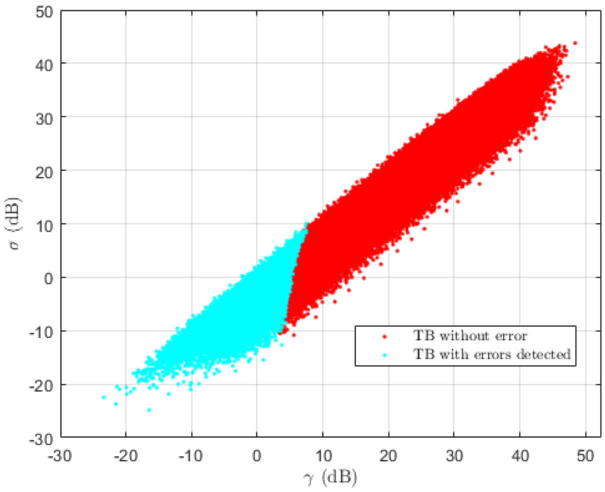
Results will depend on the distribution of both regression parameters, which in turn are function of the specific PDP and Doppler frequency.

As shown in Fig 4, approximately the same average BLER is obtained by both regression averaging and simulation. This figure illustrates the importance of σ as it is the distinguishing element between both channels. Apart from this, it is especially relevant the case of the channel with 400 ns of delay spread, which is longer than the cyclic prefix of OFDM. Hence, there is a noise floor due to ISI which is detected by the logistic regression and the adequate noise measurement.

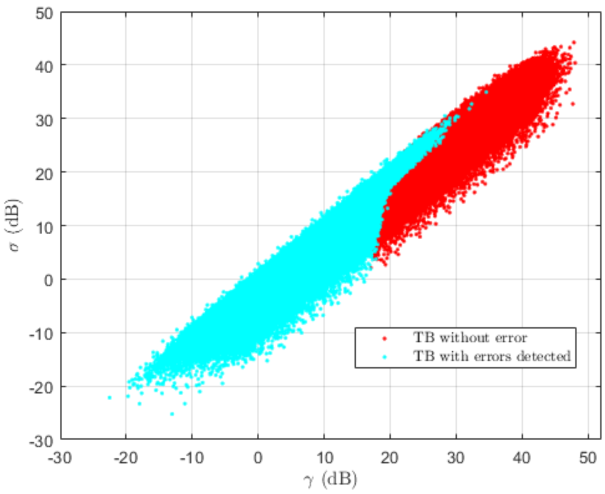
Fig. 5 shows a comparison between the proposed models. As expected, the highest the MCS is, the worse performance both regression models have. Nevertheless, it is observed that the regression fits better using model A than model B, as we use different models per MCS.

B. MCS selection

Probably, the most useful application for the instantaneous BLER prediction model is its use in AMC. In short, AMC algorithm decides the most accurate MCS in order to keep



(a) MCS = 10



(b) MCS = 26

Fig. 3. Scatter plot of data used to train regression for TB size of 6 PRBs.

the BLER below a predefined target which depends on the service, that is,

$$MCS = max\{i, \quad B_i(\gamma, \sigma) < BLER_T\} \tag{7}$$

where $BLER_T$ depends on the service, being 0.1 for eMBB services and 10^{-5} for URLLC services.

As illustrated in Fig. 6, this algorithm can track the channel by selecting robust MCSs when there is a fading and high efficient ones as the SINR improves. Observed delay of one transport block between SINR and MCS is due to the causal decision. AMC performance has a high dependence with the coherence time, being reduced as Doppler shift grows.

Spectral efficiency is one of the most characteristic statistic to measure the performance of AMC. In Fig. 7, it is shown the reduction of performance as Doppler increases. In this case, it is not appreciable the difference between model A and model B.

V. CONCLUSIONS AND FUTURE WORK

In this work, it has been introduced a technique for BLER prediction based on logistic regression. Furthermore, two possible models have been contrasted. Although for the average BLER the differences between them are appreciable,

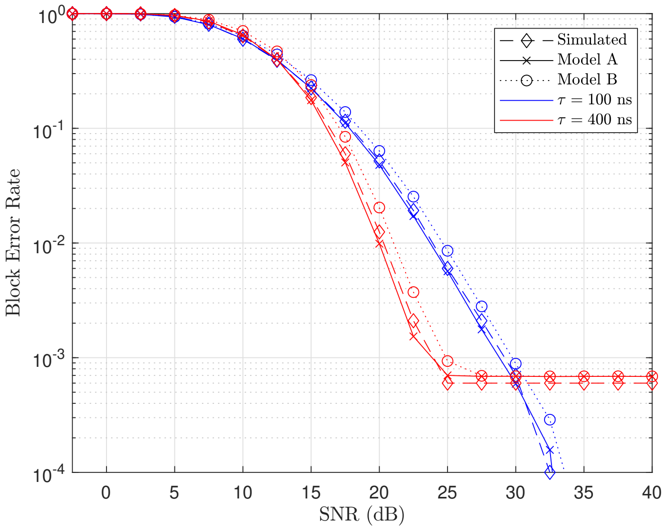


Fig. 4. Comparison between simulations and predictions using a TDL-A with $f_D = 50$ Hz and MCS = 17.

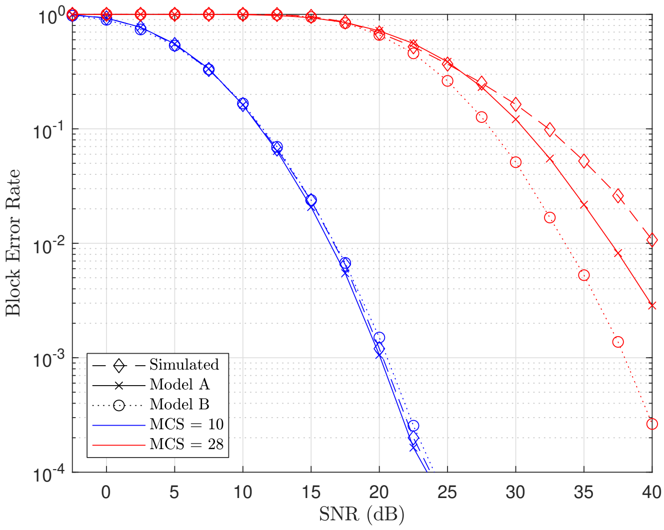


Fig. 5. Comparison between simulations and predictions using a TDL-A with $f_D = 50$ Hz and $\tau_s = 150$ ns.

error prediction by model B is low enough not to make any significant difference in AMC application. Therefore, the advantages for this second model in terms of memory make the difference for this application.

However, the method can be improved to reduce the effect of causality in the MCS decision. Techniques such as time series prediction could allow a better decision and, therefore, a higher spectral efficiency. In addition, the regression model could be generalized to include the TB size as feature.

Acknowledgements

This work has been supported by the Spanish Government and FEDER under Grant TEC2016-80090-C2-1-R (Ministerio de Economía y Competitividad) and Beca de Colaboración 19CO1/008714 (Ministerio de Educación y Formación Profesional), by the Junta de Andalucia under Grants P18-RT-3175 and P18-TP-3587, and by the Universidad de Málaga.

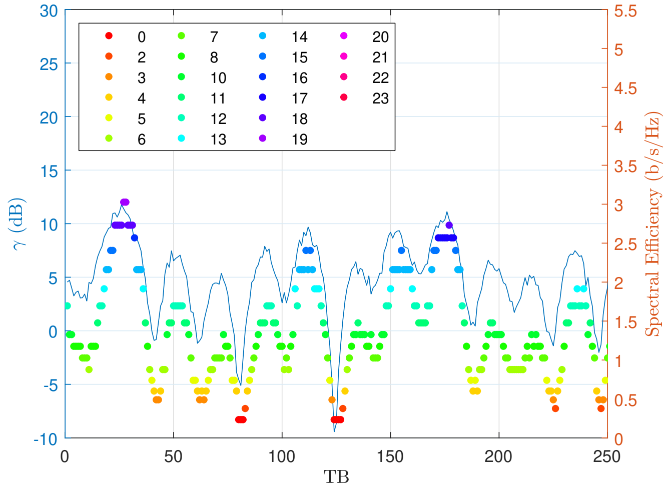


Fig. 6. The MCS decision for $BLER_T = 0.1$ based on model A for a TDL-A with $f_D = 50$ Hz, $\tau_s = 150$ ns and $\bar{SNR} = 7.5$ dB.

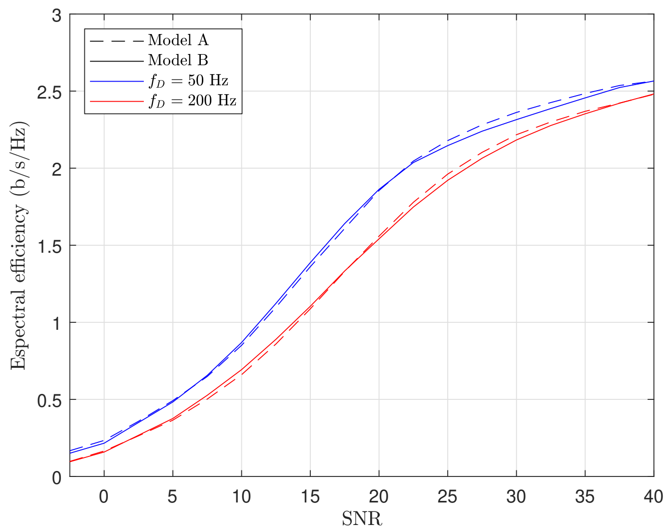


Fig. 7. Comparison of spectral efficiency for $BLER_T = 0.1$ between model A and model B and different f_D using a TDL-A channel with $\tau_s = 100$ ns.

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