Gaussian Process Regression for Feedback Reduction in Wireless Multiuser Networks

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***Abstract*—Periodic Channel Quality Indicator (CQI) feedback consumes much of the uplink resources. In scenarios such as urban festivals, sport events, and Olympics football World Cups, which pose additional challenges to the wireless networks due to the heavy traffic load, channel estimation strategies have to be implemented to overcome the problem of signalling overhead while satisfying certain performance bounds. To reduce the CQI feedback overhead, we propose a limited feedback selection scheme. The proposed scheme permits the Base Station (BS) to obtain CQI from a subset of users under substantially reduced feedback overhead and estimate the channel for the remaining users. We cast the problem of CQI estimation by exploiting the theory of Gaussian Process Regression (GPR) which benefits from the correlation property of the macroscopic shadow fading. I.e., users that are close to each other have a correlated channel. The results show that with the proposed approach, a significant reduction in feedback is achieved while keeping the BLock Error Ratio (BLER) below 10% threshold.**

***Index Terms*—5G, channel quality indicator, Gaussian process regression, overhead feedback reduction, channel estimation.**

I. Introduction

Future mobile cellular networks are envisioned to provide high data rates and an increased number of users [1]. In view of this rapid growth, most mobile network operators are also affected and numerous technologies are currently being explored to evolve to the future 5G networks. According to Cisco, with the prospect of billions of connected devices, the average mobile traffic is expected to increase 7-fold by 2021 when compared to 2016 [2]. Many reasons are driving this trend: as opposed to normal operating conditions, heavy crowd events such as sports events, mass entertainment gatherings, and public demonstrations are example scenarios posing a significant amount of signalling overhead to the Base Station (BS). Signalling includes the Channel Quality Indicator (CQI) feedback sent by the users, providing necessary information such as Modulation and Coding Scheme (MCS) for proactive radio resource allocation. The control signalling overhead is a relevant challenge for future 5G networks, [3], [4], [5].

The CQI feedback overhead problem becomes harder in case that the number of users increases [6]. In [7], [8] we proposed schemes based on the Gaussian Process Regression (GPR) method, which aim at avoiding unnecessary feedback processing, while a target threshold of BLock Error Ratio (BLER) is satisfied.

In [9], we extended our work to non-static users and showed the effects of GPR CQI estimation for various user speeds. We proposed an analytical optimization in the choice of users which enhances the spatio-temporal correlation of the wireless channel. Like any other prediction algorithms, GPR generates estimation errors. The estimation error causes an the BS to choose inaccurate MCS level. The system performance reduces if a lower MCS level is selected, but increases the reliability by decreasing the BLER. If a higher MCS level is selected, the reliability decreases by increasing the BLER. To mitigate the estimation error, we proposed in [8], an optimization method for SNR-CQI mapping by introducing an offset, adjusted adaptively according to the estimation accuracy relative to the user density. In this paper, we deal with the CQI feedback reduction and quantify the amount of the reduced feedback. We propose two user selection algorithms, corresponding to normal and heavy crowd events.

The rest of the paper is structured as follows. In Section II, we provide a literature review related to feedback reduction and channel prediction mechanisms. Section III, introduces the considered system model and deals with reducing the feedback overhead using the proposed CQI estimation method. Results are discussed in Section IV. Section V concludes our work and summarizes the basic insights, poses suggestions and identifies directions for future research investigations.

II. Related Work

The anticipatory, or proactive allocation of wireless channel resources is typically used to improve communication performance. Since the channel condition of a user changes due to the various environments, the BS uses link adaptation by means of adaptive MCS. Adaptive MCS is based on the CQI. It is used for rate adaptation and scheduling. For this reason, each user is required to send the CQI to the BS. However, the amount of feedback increases as the number of users in the system increases, and obviously, it becomes serious in uplink overhead.

In [10], the authors propose a channel feedback model in which the derived CQI is calculated according to the predicted Signal-to-Interference-and-Noise Ratio (SINR). Their evaluation results show that the SINR prediction using extrapolation is degraded at high user speed. They conclude that when a user moves at low speed in urban areas, a high gain can be expected when using the channel feedback model with SINR prediction as compared to the feedback model without SINR prediction.

In [11], the authors propose an adaptive CQI prediction scheme to estimate users' channel quality variations at the BS side. They focus on reducing the time-domain feedback overhead using the GPR for different user speeds. They have shown that the feedback overhead cannot be overlooked as the number of users keep increasing and needs additional restriction in the time domain. However, there are solutions in the frequency domain to limit the impact of signalling feedback overhead on the uplink. A BS-side rate estimation method is presented in [12]. It enables the system designers to reduce the feedback overhead at the expense of more computations at the BS.

In [13], the authors study and apply several channel predictors under realistic delay and channel assumptions used to compensate the performance loss due to the outdated CQI. The predictor takes into account the Doppler shift of each user for more accurate estimation. For the studied scenarios, the results show that at higher Doppler shifts, considerable performance gains can be reached when the CQI delay is in a lower practical regime. The procedure, although well established, might lead to an erroneous prediction.

In [14], the authors propose a cross-layer Dynamic CQI Resource Allocation (DCRA) scheme at the BS-side. DCRA adaptively chooses the users which are to send feedback to maintain their QoS constraints. It first derives the optimal average feedback window values based on the user speed and service class for a target packet error rate, then allocate resources on a frame basis. Their goal is to select a subset of users to send CQI feedback among all the users to be scheduled in the next frame while keeping the system throughput at its maximum. In [15], the same authors expand their works by using a linear predictor implemented at the BS side and compensating errors by changing the prediction windows based on the users packet loss. All results showed that the proposed opportunistic method improves the system throughput in terms of BLER especially in high speed scenarios, and helps to maintain the QoS of delay constraint of time-sensitive applications.

In [16], the authors propose a non-predictive signalling reduction strategy in which the amount of bandwidth consumed for the signalling can be significantly reduced by selecting the users with the lowest average Signal-to-Noise Ratio (SNR) to periodically feedback their CQI to the BS. The proposed strategy is more beneficial at low values of the user velocity where the incurred throughput losses are minimal.

In [17], the authors identify a trade-off between the downlink performance and uplink overhead. Such a trade-off is determined by various feedback allocation strategies, the number of the users, and their channel qualities with respect to the average cell channel quality. They study the impact of the proposed method on an LTE network and show that dynamically allocating the resources can be beneficial for the network. In [18], the authors propose a best-M feedback scheme which involved selecting the user and rate on the basis of feedback-conditioned good-put computed by the BS. The policy exploits the structure of the information fed back by the proposed scheme and the correlation among the sub-channel gains.

III. SYSTEM MODEL

In wireless communications, the channel conditions are determined by three factors: path-loss, shadow fading and multipath propagation. Each factor has different characteristics. Shadow fading is spatially characterised. The correlation changes according to the environment. When the users are close to each other, they experience similar path-loss and shadow fading.

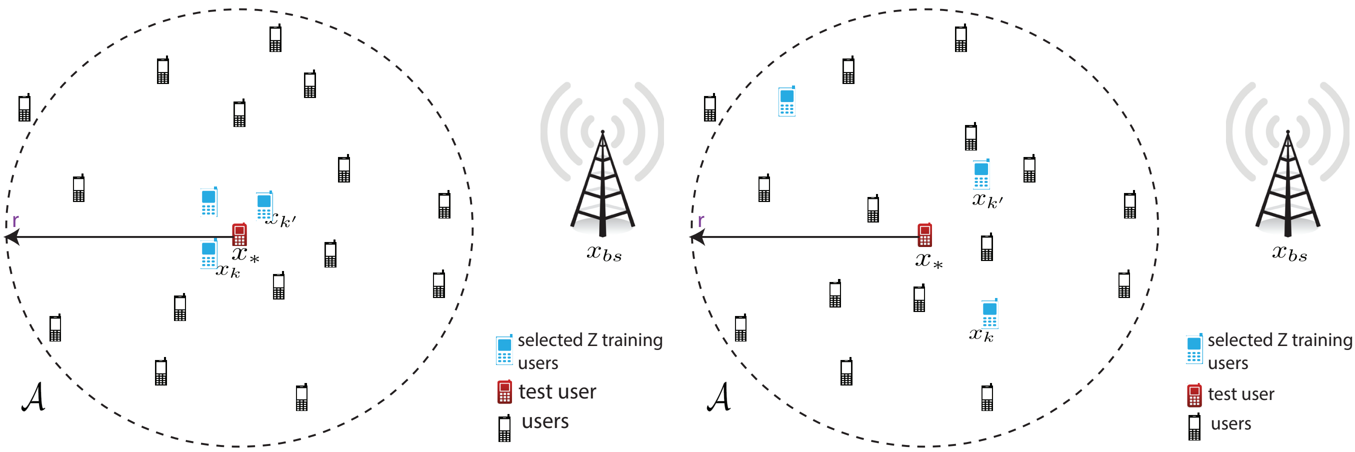
Let

$$P(x_k) = P_{TX} - 10\alpha\log_{10}(\|x_{bs} - x_k\|) + X_{x_k} + n_k \quad (1)$$

be a random variable denoting the value of the noise corrupted received power at user k in a large-scale fading environment. Here, P_{TX} is a constant that captures antenna and other propagation gains, α is the path-loss exponent, X_{x_k} is the location dependent shadow fading such that $X_{x_k} \sim \mathcal{N}(0, \sigma_{\mathcal{X}}^2)$, $\sigma_{\mathcal{X}}$ is the standard deviation in dB of the shadowing loss, x_{bs} is the BS location, $x_k \in \mathcal{A} \subseteq \mathbb{R}^2$ is the user location, $\mathcal{A}$ denotes the region of interest (ROI), and $n_k \sim \mathcal{N}(0, \sigma_n^2)$ is a zero mean additive white Gaussian noise with variance σ_n^2 of noisy observation. Figure 1 illustrates the system model.

We assume that the users are locally distributed based on a Poisson point process with user density λ_K in a circle of radius r, such that $\Phi = \{x_k \in \mathcal{A} = \pi r^2; k = 1, ..., K \in \mathbb{N}\}$ represents the location of the users. The BS calculates the SNR $\gamma(x_k) = P^{lin}(x)/W^{lin}$ and determines a quantized CQI value $\{Q_j\}_{j=0}^{J=15}$ which is the index of the MCS. Here, $P^{lin}(x)$ and W^{lin} are the received power and receiver thermal noise both measured in a linear scale, respectively. The MCS varies according to the channel conditions. To determine an appropriate MCS, the user should measure its SNR or its channel conditions, quantize it, and feed the measured CQI back to the serving BS, so that it can determine which MCS has to used. Since a CQI feedback contains the averaged channel condition, the effect of multipath, i.e., small scale fading, will disappear due to the averaging. Each MCS has a corresponding data rate of $R(Q_j)$. User k can reliably decode the data only if $\gamma(x_k)$ falls above a threshold value of SNR; else, an outage occurs [8].

The CQIs which are fed back to the BS cause feedback overhead. If n users are close enough to each other, they will experience similar channel condition, so they will send similar CQI feedback to the BS. However, in this case, only one representative user may need to send the CQI feedback instead of all, and the reduction of CQI feedback by $1/n$ could be achieved. If the number of users increases, the overhead becomes larger. To tackle this, we present a GPR approach to estimate the CQI at an observed desired test user x_* reducing thus the number of the needed CQI reports. Specifically, given



(a) closest user selection (b) random user selection

Fig. 1: System model scenarios.

a collection of corrupted observations from users and given a set of hyperparameters $\theta = [P_{TX}, d_c, \alpha, \sigma^2_{\mathcal{X}}, \sigma^2_n]$, the best estimate for $\check{P}(x_*)$ can be calculated from the mean power

$$\mu(x_k) = P_{TX} - 10\alpha\log_{10}(\|x_{bs} - x_k\|), \tag{2}$$

and the correlation function

$$C(x_k, x_{k'}) = \sigma^2_{\mathcal{X}} \exp\left(\frac{-\|x_k - x_{k'}\|}{d_c}\right), \tag{3}$$

where d_c denotes the decorrelation distance of the shadowing [19]. The estimated mean received power at x_* is then expressed as [20]

$$\check{P}(x_*) = \mu(x_*) + \mathbf{C}^T_{*,\mathbf{x}}(\mathbf{C}_{\mathbf{xx}} + \sigma^2_n\mathbf{I})^{-1}(\mathbf{y} - \mu(\mathbf{x})), \tag{4}$$

where $[\mathbf{C}_{*,\mathbf{x}}]_k = C(x_*, x_k)$ is the $K \times 1$ vector representation of the cross-correlation, and $[\mathbf{C}_{\mathbf{xx}}]_{kk'}$ is the $K \times K$ covariance matrix representation of $C(.,.)$ evaluated pairwise across the elements of x_k and $x_{k'}$. We assume that the BS knows the location information of the users. Else, there will be a certain overhead to find the location of the users. Here, we do not consider this overhead.

The correlation depends on the density and the location of the users and has a large influence on the performance. Therefore, the users with the highest correlation have to be selected. We consider two different user selection schemes. A subset $Z \sim Poiss(\lambda_Z) \subseteq K$ of users is selected by the BS either randomly, Figure 1b, or being in the closest vicinity to the test user, Figure 1a. Using the information obtained from Z candidate users, we estimate the CQI for the remaining test user x_*.

TABLE I: Simulation Parameters

Parameter	Value	Parameter	Value
α	2	x_{bs}	[200 0] m
d_c	40 m	σ^2_n	0.01
$\sigma^2_{\mathcal{X}}$	10 dB	r	50 m
W	−57 dB	P_{TX}	0 dB

IV. Simulation Results

When reducing CQI feedback, the challenge is how much it could be reduced whilst maintaining the required BLER or rateloss threshold. In this section, the simulation results for the two proposed scenarios are presented. The results verify that the proposed method can effectively reduce the CQI feedback overhead, given the parameters in Table I. In order to make the proposed framework applicable, it is assumed that the small scale fading has been averaged out. We model a circular ROI with the size of 7850 m^2. All the curves are averages over 10^4 random realization of users locations.

Figure 2 shows the behaviour of the proposed GPR estimation method for two different choices of training data sets. For each case, there are three curves, each corresponding to a particular density of λ_K. The solid lines and dashed lines correspond to the random user selection and the closest user selection, respectively. There are considerable gains for both schemes. For all densities of $\lambda_K = 0.05, 0.07, 0.09$ the BLER decreases as the density of the training data set λ_Z increases, where the majority of the performance gain stems from the higher correlation of the neighbouring users. In the case of a random user selection, the BLER is gradually decreasing independent of λ_K, until λ_K is reached. However, in the case

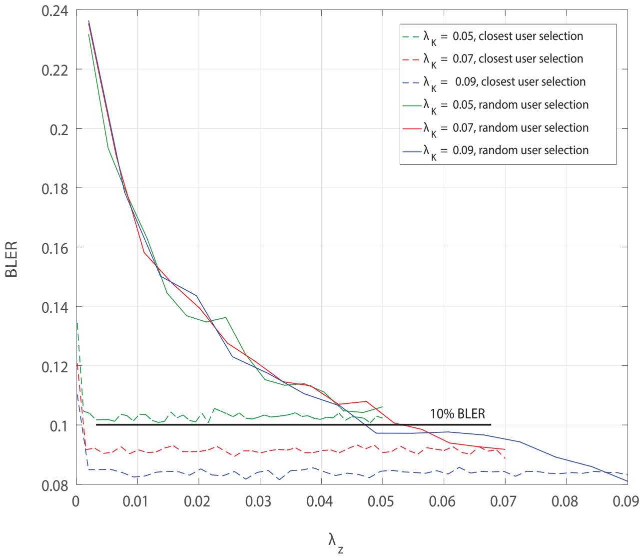


Fig. 2: BLER versus density of selected users.

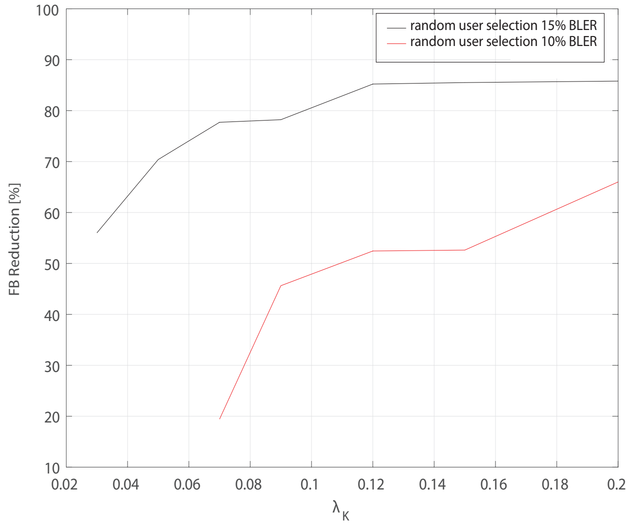


Fig. 4: Feedback reduction versus density of users in ROI.

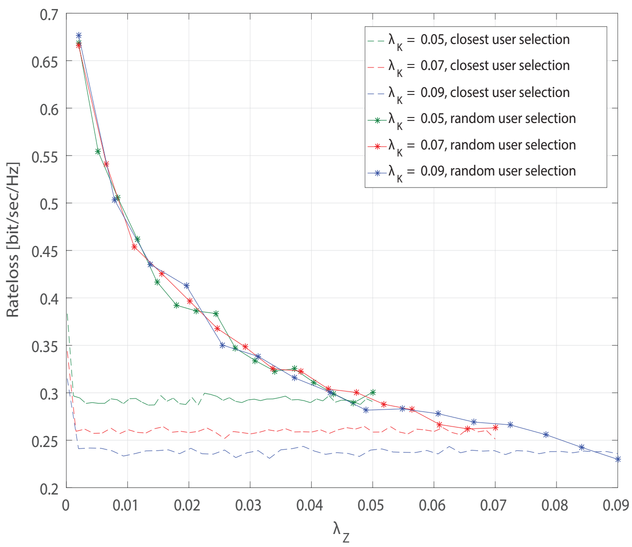


Fig. 3: Rate Loss versus density of selected users.

of a closest user selection, the BLER is sharply flattening at an asymptotic value denoting that the users are close enough and adding more information from additional users does not improve the performance but only complicates the estimation processing. In this case the three curves are not overlapping. The reason is that the distances of the training users from each other and from test user depends on λ_K. The higher λ_K is, the more the correlation becomes. As an example scenario consider a small density of $\lambda_K = 0.05$. In this case, even if all the users with the density of $\lambda_Z = \lambda_K = 0.05$ are selected, there will be still smaller spatial correlation than the case of $\lambda_K = 0.09$ with the training density of e.g., $\lambda_Z = 0.01$.

The CQI estimation error is a factor that has a negative impact on system performance and channel reliability. The loss of accuracy in CQI estimation leads to loss in transmission rate, either by requiring retransmission due to the overestimation or by wasting radio resources due to the underestimation. We define the rate loss as a difference between the actual and the estimated rate. Figure 3 depicts the rate loss as a function of selected training user with density of λ_Z. The rate loss is indicated by $*$ for the random user selection and a dashed line for the closest user selection. All the curves show the same behaviour meaning that with increasing λ_Z, the rate loss decreases. A large training can lead to less errors in estimation of the CQI values, because the users are closer to each other and there is spatial correlation.

To examine the amount of CQI feedback saving, we calculate the percentage of feedback saving by $(1 - \frac{\lambda_Z}{\lambda_K}) \times 100$. Figure 4 shows the reduction of feedback amount versus the density of the users in the ROI for the case of random user selection. From the figure we observe that the CQI estimation method allows high gains of reduction in feedback signalling for both BLER thresholds imposed at 10% and 15%. The reduction is higher for 15% BLER as expected. As the number of users increases, our proposed scheme will show more gain.

V. Conclusion

In this paper, we proposed an estimation-based CQI scheme which reduces significantly the CQI signalling overhead. As a consequence, the quality of the link adaptation at the uplink is increased. The main idea is that in heavy crowd events, where users are close to each other, some representative users transmit CQI feedback. The proposed method performs better in case the users are closer to each other as the spatial correlation of the communication channel is higher. We presented how to select a subset of users to send the CQI among all the users, while keeping the system throughput at a maximum. To estimate the users' channel quality with good accuracy, we proposed a GPR technique which is able to model the changes in the user's channel. The results show that an anticipatory and proactive allocation is practicable which offers to generalize the approach to a multi-cell scenario with interference consideration.

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