HSDPA Link Adaptation Improvement Based on Node-B CQI Processing

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Abstract — **In this paper HSDPA link adaptation (LA) based on Channel Quality Indicator (CQI) reports is optimised. A pre-processing of the last received CQI reports is done before the execution of the LA algorithm in the Node-B in order to obtain more profitable channel quality estimations and hence improve the LA performance. Different types of processing techniques are presented and assessed, considering from the simplest sample averaging to some more elaborated predictive algorithms. Results demonstrate that a non negligible enhancement in the LA performance can be obtained if medium and high speed users are considered.**

I. Introduction

High Speed Downlink Packet Access (HSDPA) and its uplink counterpart HSUPA have been recently standardized in 3GPP to improve the performance of previous UMTS systems. HSPA standards aim at increasing the downlink packet data throughput while efficiently sharing the available radio resources. HSDPA achieves these objectives by means of adaptive modulation and coding (AMC), fast scheduling mechanisms (each TTI or Transmission Time Interval of 2 ms) and a Hybrid ARQ mechanism. A good survey of HSPA principles can be found in [1].

Link adaptation (LA) and scheduling are processes of paramount importance to optimise HSDPA system performance. However, they have not been standardised to propitiate competitiveness among vendors and therefore many investigations are done in these fields.

In HSDPA, the user equipment (UE) reports periodically to the Node-B its experienced downlink channel quality by means of the Channel Quality Indicator (CQI) [2]. Numerically CQIs are integers extending from 1 to 30, increasing its value when channel quality augments.

Usually LA is based on these CQI reports in such a way that the resources allocated to one user are at most or even exactly the corresponding to its last reported CQI (or a slightly modified version which takes into account the actual availability of power, codes, etc.). Each CQI can be translated into a combination of transmission parameters since [2] establishes a relation between each CQI and a concrete value of the transport block size (TBS), number of simultaneous channelisation codes, modulation and code rate.

However, some time passes since the CQI is measured by the user until this information is employed by de Node B to perform a downlink transmission. In particular, if the minimum CQI reporting period (2ms) is considered, this delay is around 7ms. Due to the fast radio channel variations and the existence of this non negligible delay, the last CQI report sent by the user may not be reliable to carry out the LA, most of all when the user velocity is high. The effect of this inaccuracy on the system performance has been studied in several papers as [3] and [4], showing that this imprecision is critical for the system performance. In consequence, some additional mechanisms are needed to correct the CQI inaccuracy or to extract useful information from the inaccurate CQI reports. A method to correct the reported CQIs employing the ACK-NACK ratio is proposed in [1] and [5], while [6] presents a strategy which reduces the employed CQI, thereby increasing data protection, when the time elapsed since the last CQI report increases. All these algorithms prevent the system from making mistakes in LA but are unable to follow the channel state and therefore do not maximise the system capacity use.

The main objective of this paper is to optimise link adaptation via an estimation of the channel quality experimented by the UE in the next downlink transmission (in the form of a CQI) based on the knowledge of the past CQIs. With this aim, different types of pre-processing of the CQI reports received by the Node-B are presented and assessed.

The rest of the paper is organised as follows. In Section II the employed system level simulation tool is described. In Section III different techniques of CQI pre-processing are presented, comparing its capacity to predict the future channel state. The effect of the pre-processing techniques on HSDPA LA performance is evaluated in Section IV. Finally, the main conclusions are drawn.

II. Simulation Environment

Simulation in this paper has been conducted with the emulator presented in [4], which is part of the SPHERE simulation platform described in [7]. In Section III the emulator has been employed to obtain CQI report traces whereas in Section IV it has been used to evaluate the system level performance of CQI processing. Table I summarises the most important parameters of the simulated scenarios.

TABLE I MOST IMPORTANT SIMULATION PARAMETERS

Parameter	Value
Load	1 user
Simulation time	1800 s (vehicular scenarios) , 7200s (pedestrian scenarios)
Cell radius	1 Km
Number of cells	7 (central cell and one tier of interferers)

UE Speed	50 km/h (vehicular) or 3 km/h (pedestrian)
Node-B Tx Power	43 dBm
CPICH Power	33 dBm
Orthogonality factor	0.8
Path Loss model	$L(dB) = 128.1 + 37.6\log_{10} d(Km)$
Shadowing model	Lognormal distribution, 8dB std dev
Fast fading model	$f_\psi(\psi) = \frac{27}{2}\psi^2 e^{-3\psi}$
UE category	10
Scheduling algorithm	Round Robin
HARQ SAW processes	6
Retransmissions	Not considered

III. CQI PROCESSING

In this section the variability of the CQI reports is studied. Next, some processing strategies are presented and its ability to perform effective CQI estimations is compared.

A. CQI variability analysis

In HSDPA the UE performs periodical CPICH *CINR* (Carrier to Interference plus Noise Ratio) measurements, mapping each calculated *CINR* to a concrete CQI whose transmission parameters would ensure a *BLER* (Block Error Rate) equals to 10%. Therefore, the CQI variability is directly related to the *CINR* variability, the only difference is that the CQI is like a quantization of the *CINR* with 1 dB steps.

The *CINR* is usually calculated in HSDPA with the following equation:

$$CINR = \frac{P_{CPICH} \cdot \Gamma \cdot L \cdot S \cdot F}{(1-\alpha)P_{total} L \cdot S \cdot F + \sum_{i=1}^{I} P_{total_i} L_i S_i F_i + N} \quad (1)$$

where the numerator contains the useful power received in the UE antenna and the denominator consists of three terms: the first one represents intra-cell interference, the second one represents inter-cell interference and the latter, *N,* represents the thermal noise. P_{CPICH} is the CPICH power, P_{total} is the total power transmitted by the serving Node-B, P_{total_i} is the total power transmitted by each one of the *I* interfering Node-B. *L*, *S* and *F* represent the path losses, shadowing and fast fading respectively. L_i, S_i and F_i are the path losses, shadowing and fast fading of the link between the user and the *i*-th interfering Node-B. Γ is the power offset between the CPICH power and the HS-PDSCH power. Finally, α is the orthogonality factor ranging from 0 to 1, meaning $\alpha = 1$ a perfect orthogonality.

The following factors explain the *CINR* variability:

1) L: Its dynamic margin depends on the cell radius and its variation rate depends on the mobile speed.

2) *S:* Its dynamic margin is fixed in the simulations (8dB standard deviation) and its variation rate is clearly related to the mobile speed (*S* is decorrelated after 1s for vehicular users at 50 km/h and 24s for pedestrian users at 3 km/h).

3) F: Its dynamic margin is fixed in the simulations (2.7dB standard deviation) but its variability depends on the speed (coherence time equals 2ms for 50 km/h and 32 ms for 3km/h).

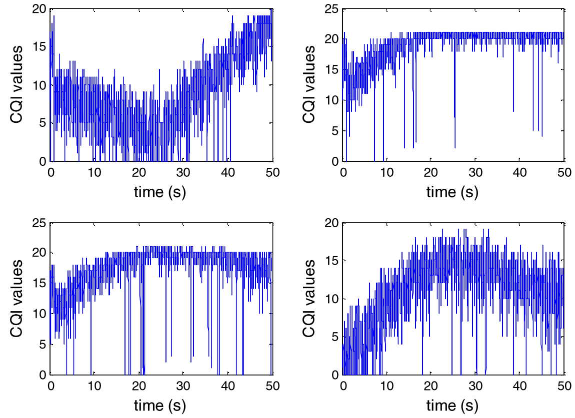

Fig. 1 CQI traces for pedestrian users during 50 seconds

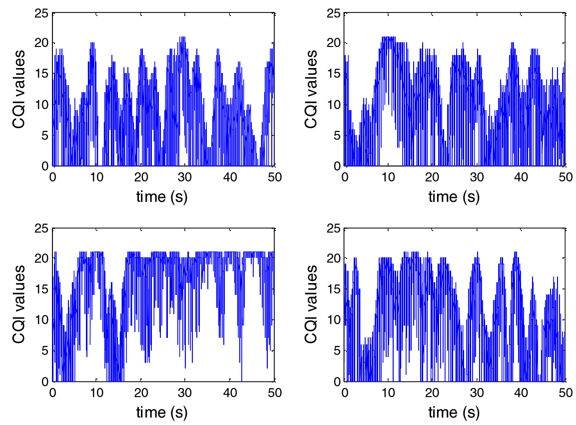

Fig. 2 CQI traces for vehicular users during 50 seconds

4) α *:* A perfect characterization of the *CINR* would require a variable orthogonality factor [8]. For the sake of simplicity, in this paper a fixed value of 0.8 is used.

5) P_{total} *:* The power transmitted by the Node-B is not constant. In low load scenarios, the transmitted power can change in a non negligible way from one TTI to another, introducing impulsive interference and hence short term CINR and CQI variations. However, in high load scenarios, this variation is small and a high almost-constant interference is expected to be received. To conduct this assessment a high loaded network has been considered.

To resume, in the short term fast fading variations and transmitting power fluctuations are the most prominent factors. In the mid term, shadowing effect is quite significant whereas the average fast fading and power fluctuations effect is zero. Finally, in the long term, the path losses changes are the only important factor. In this paper the short term variation is the most important one since the main objective is to perform short term CQI estimations.

Next, some CQI traces are presented to show CQI variability. Two figures have been plotted analysing different scenarios. Fig1 considers pedestrian users moving at 3 km/h and Fig2 considers vehicular users moving at 50 km/h. Pedestrian and vehicular traces are similar but the main difference is the faster variation in the CQI vehicular traces.

These traces have been obtained from a saturated scenario, what means that users always have information pending for transmission. For this scenario and having into account the considered orthogonality factor, the ratio between useful power and own cell interference determines a maximum CQI value, which in this case is 21 as corroborated in the figures.

B. Future CQI estimation strategies

According to the methodology of processing, three different classes of estimation strategies have been analysed. The first one is the simplest scheme which takes the last reported CQI as the future CQI estimation (mode 1). The second class comprises different strategies based on the filtering of the last n reported CQI, being this filtering linear (modes 2, 3, 5, 6) or non linear (mode 4). The third class is composed by predictive schemes which perform an adaptive filtering of the last reported CQIs to obtain a prediction of the future CQI (modes 7, 8).

Next, all the processing modes are explained:

1) *No processing* (No proc): the basic strategy in which the last reported CQI is directly the future estimation.

2) *Exact averaging* (Averaging):the estimation is obtained averaging the last n reports.

3) *Smoothed averaging* (Smoothing): the estimation is obtained smoothing the reported trace of CQIs with the next formula:

$$\widehat{CQI}(k) = \left(1 - \tfrac{1}{T}\right)\widehat{CQI}(k-1) + \left(\tfrac{1}{T}\right)CQI(k), \qquad (2)$$

where $CQI(k)$ is the last reported CQI, $\widehat{CQI}(k-1)$ is the old CQI estimation, $\widehat{CQI}(k)$ is the new CQI estimation and T is the equivalent averaging period in TTIs.

4) *Median CQI* (Median): the estimation is obtained as the median of the last n reports.

5) *Weighted conservative filtering* (W.cons.): the estimation is obtained as the weighted average of the last n reports, being the weighting function linear, giving more weight to the lower CQI reports

6) *Weighted smart filtering* (W.smart): the estimation is obtained as the weighted average of the last n reports, in this case giving more weight to the newest CQI reports. Again the weighting function is linear.

7) *LMS prediction* (LMS): the estimation is the prediction performed by the LMS method [9] with one coefficient and a step size of 2e-4.

8) *LMS average prediction* (LMS avg.): in this case the reference signal is the trace of the exact CQI averaging.

C. Future CQI estimation results

In the remaining of this section the performances of all the processing methods are compared. The minimum CQI reporting period of 2ms has been considered since it is a common used value. The effect of the number of samples used in the averaging has been assessed too.

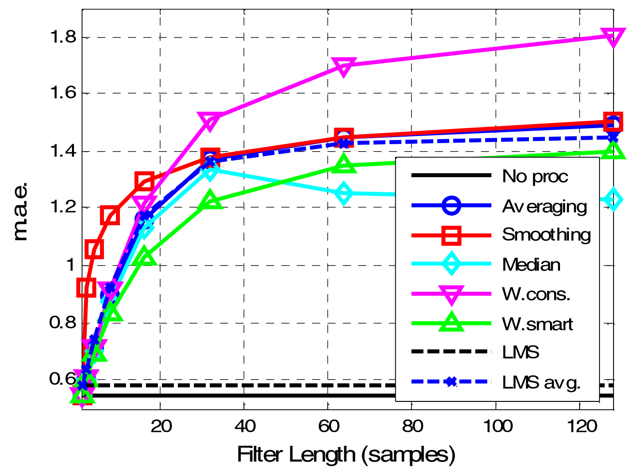

Fig. 3 Mean Absolute Error of the CQI estimation modes for different filter lengths. Pedestrian users

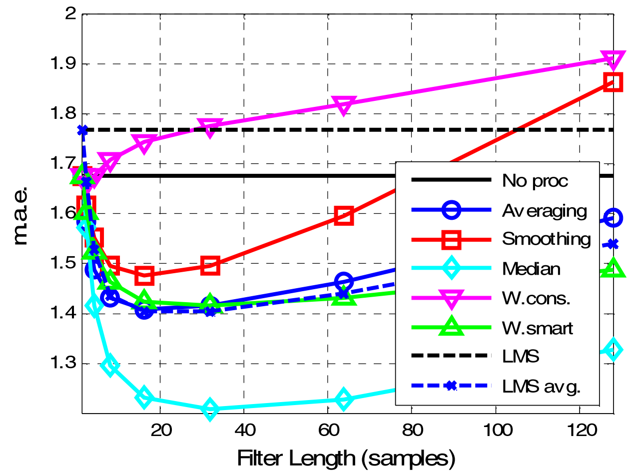

Fig. 4 Mean Absolute Error of the CQI estimation modes for different filter lengths. Vehicular users

Pedestrian users moving at 3 km/h and vehicular users moving at 50 km/h have been studied.

First of all, the mean absolute error (m.a.e.) of the estimations is shown in Fig 3 and Fig 4.

In the pedestrian environment (Fig. 3) the best results are achieved by the basic method. On the other hand, in the vehicular environment (Fig 4) this mode can be highly improved thanks to the use of processing techniques. The optimum filter length depends on the processing technique but is around 16-32 samples. This divergence between vehicular and pedestrian is explained by the different fast fading variability in each case. In the pedestrian scenario the channel does not practically change in 7 ms and hence the basic mode behaves well. Besides, all techniques based on averaging introduce an artificial longer delay in the channel tracking that can not improve the basic method. In a vehicular scenario channel changes faster and the basic mode is not able to track these variations. It is necessary to perform some kind of processing to obtain a better estimation of the mean future channel quality, which results in a better m.a.e.

Focusing on the vehicular scenario, one interesting observation is that exact averaging behaves better than smoothed averaging. In the latter, impulsive variations of the CQI affect the CQI estimation for a longer time. Regarding the non linear filtering methods, the median CQI scheme presents the best performances as compared with the other algorithms since this scheme removes the effect of deep fades in the CQI due to the fast fading, avoiding the pernicious effect of these outliers. The weighted conservative filtering performs conservative choices, not accurate choices, and therefore presents high m.a.e. values. The weighted smart scheme presents good results, similar to the averaging scheme due to its inherent ability to track the channel quality.

The predictive schemes behave similar than their non predictive counterparts. The LMS behaves like the basic method and the LMS applied to filtered traces behaves similar to the exact averaging. The simple LMS prediction performance is lower than it could be expected by the reader due to the low predictability of the series under study.

However, although the m.a.e. provides an interesting information about the ability of the different processing techniques to perform accurate estimations, it is not the only important factor to be considered in the LA optimisation. The success of the CQI estimation has been also analysed. A CQI is optimally estimated if the CQI selected to transmit and the CQI experienced in the reception are equal. An optimistic CQI estimation occurs when the CQI used in the transmission is higher than the experienced it the reception and therefore the information is not properly received. Finally, a conservative CQI estimation is done when the experienced CQI is lower.

Next figures show the ratios of optimal, optimistic and conservative CQI choices for the considered algorithms. The same filter length of 64 samples has been employed for the pedestrian and vehicular scenarios. As expected, filtering increases the conservative CQI choice. This effect is more visible with the most conservative algorithms. Predictive schemes show a similar effect but less pronounced.

As it can be observed in Fig. 5, in a pedestrian scenario the basic mode of no processing behaves really well. All the other methods produce a decrease in the optimal choice ratio and an increase in the optimistic and/or conservative ratios. In the vehicular environment the basic mode presents a poorer behaviour while other methods obtain more accuracy, like in the median case, or increase the ratio of conservative choices.

IV. SYSTEM LEVEL SIMULATIONS

The results of Section II measure the accuracy of the CQI estimations and how the different algorithms can change the ratio of optimistic, optimal and pessimistic CQI selections as compared with the basic mode. In this section the effect of the CQI processing technique on the LA performance is evaluated in a simulated high-loaded network.

The simulation considers a single user per cell since in such a scenario the results are independent of the scheduling algorithm. The high load has been emulated forcing the users to have always data pending for transmission in the Node-B. Pedestrian and vehicular users were simulated.

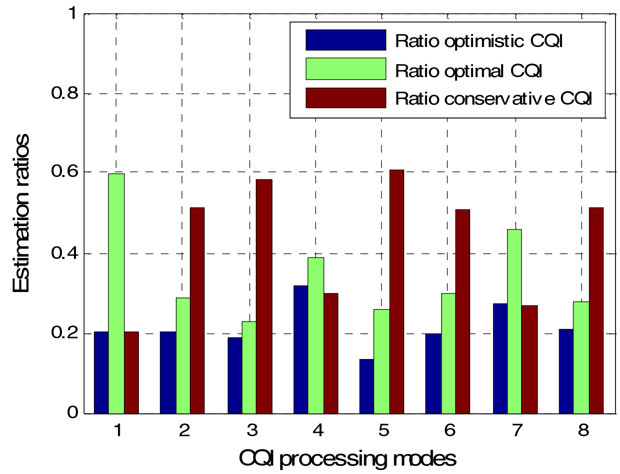

Fig. 5 Ratio of optimistic, optimal and conservative CQI selection for each processing mode. Pedestrian users.

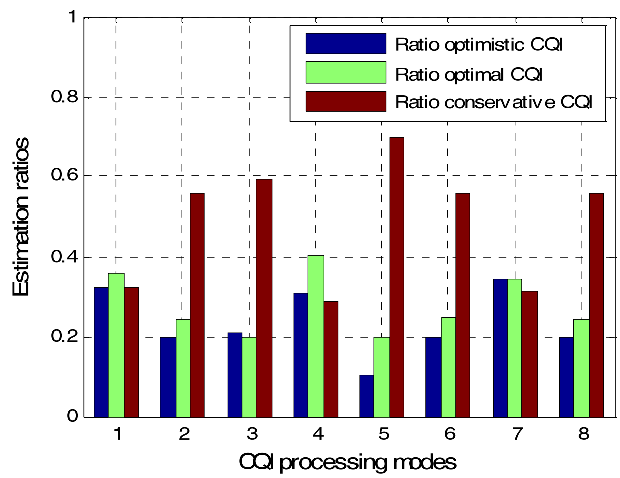

Fig. 6 Ratio of optimistic, optimal and conservative CQI selection for each processing mode. Vehicular users.

Two parameters have been evaluated, namely throughput, i.e. bits transmitted per second, and block error rate (BLER), defined as the ratio between the number of blocks correctly received and the total number of transmitted blocks.

In Section II it was concluded that the processing of the CQI reports can enhance the basic channel quality estimation but only in a vehicular scenario. The results obtained in the system level simulations corroborate this idea. As shown in Fig. 7 and Fig. 8, the maximum throughput for the pedestrian case is achieved with the basic method whereas in the vehicular scenario some gain can be obtained when processing is done.

With respect to the vehicular case, five of the proposed techniques obtain better results than the basic mode. LMS with filtered reference signal provides the best results (5.8% improvement) but the use of exact averaging and median modes entails a similar gain, as can be observed in Table II. Therefore, the gain is due basically to the averaging but not to the prediction.

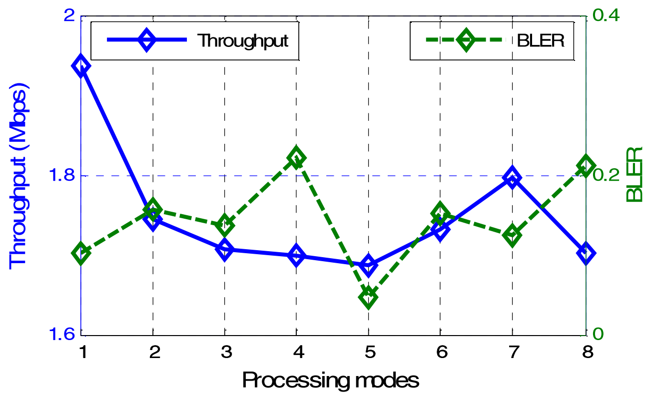

Fig. 7 Throughput and BLER in a pedestrian high-loaded scenario.

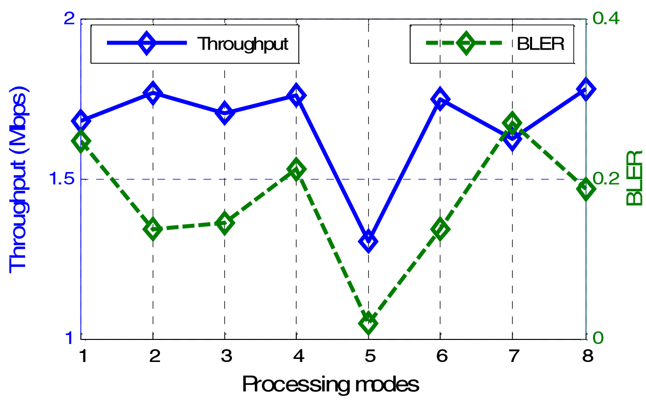

Fig. 8 Throughput and BLER in a vehicular high-loaded scenario.

TABLE II THROUGHPUT IMPROVEMENT IN THE VEHICULAR SCENARIO

Mode	2	3	4	5
Improvement (%)	5.10	1.33	4.89	-22.40
Mode	6	7	8	
Improvement (%)	4.26	-3.22	5.80	

According to the Fig. 8, and taking into account the information of Figure 6, it can be concluded that there are two ways of improving the system performance. The first one is to improve the optimal choice ratio, which is what happened with the median method. In this case, both the number of incorrectly received blocks (directly related to the optimistic choices) and the number of transmissions where the link resources are not fully profited (directly related to the conservative choices) is reduced. Therefore, the optimality as was considered in the CQI selection is highly related to throughput maximization. On the other hand, methods 2, 3, 6 and 8 accomplish the objective of improving the throughput via a more conservative CQI estimation than the basic mode. Although they reduce the optimal choice ratio and increase the conservative choices they lessen substantially the optimistic choices and hence the BLER. This decreasing in the BLER justifies the throughput improvement since fewer blocks are lost. Method 5, the more conservative, reduces the BLER but is too much conservative and its choices do not take advantage of the channel quality as other algorithms do. Finally, method 7 is unable to improve the system performance since it augments the BLER by increasing the optimistic choice ratio.

Two important matters arise from now. The first is the determination of the threshold speed in order to apply or not the CQI processing. According to simulations this threshold speed is around 16 km/h for the simulated scenarios. The second one is the evaluation of how CQI measurement errors affect the performance of the CQI processing. Again, according to simulations, assuming a 1dB standard deviation lognormal error in the *CINR* CPICH measurements it has been proven a LA performance enhancement higher than the one obtained in this paper, which was around 15%.

V. CONCLUSIONS

In this paper it has been evaluated the effect of applying a CQI pre-processing before performing LA in the HSDPA Node-B. As explained, usually the last reported CQI is the only input to the LA algorithm but this strategy can be suboptimal when the radio channel quality changes quickly. It has been demonstrated that when the UE speed is high some processing strategies can provide a better channel estimation than the last received CQI. This better channel estimation results in an increasing of the system throughput up to the 5.8% and a reduction of the BLER. On the contrary, when the UE speed is low, the basic mode outperforms other processing techniques, which is justified by the high channel coherence time. Therefore, the implementation of a CQI processing technique in a real system will require a previous knowledge of the UE speed in order to perform or not the processing technique.

ACKNOWLEDGMENT

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