Self-Optimization Algorithm for Outer Loop Link Adaptation in LTE

A. Durán, M. Toril, F. Ruiz, and A. Mendo

***Abstract*—In this letter, a novel algorithm for improving outer loop link adaptation (OLLA) convergence speed in the downlink of Long Term Evolution (LTE) is presented. The proposed heuristic algorithm adjusts the OLLA initial offset parameter based on OLLA adjustment histograms of large activity connections. The algorithm is validated with a connection-level simulator, fed with real connection traces collected from a live LTE network. Results show that average network block error rate, user throughput and spectral efficiency can be improved by properly adjusting the initial OLLA offset parameter.**

***Index Terms*—Mobile network, long term evolution (LTE), outer loop link adaptation (OLLA), self-optimization.**

I. Introduction

LINK adaptation is a key process in mobile communications systems. The aim of link adaptation is to cope with changes in radio link conditions by dynamically selecting the optimum modulation and coding scheme (MCS) for each connection. Achievable user throughput largely depends on proper MCS selection. If MCS is too conservative, instantaneous channel capacity is not fully exploited. In contrast, if MCS is too aggressive, block error rate (BLER) increases and radio link efficiency is impaired.

Most existing link adaptation schemes consist of an inner loop link adaptation (ILLA) selector and an outer loop link adaptation (OLLA) corrector. The aim of ILLA is to select the most suitable MCS based on link quality measurements. In its simplest form, it assigns an MCS to each reported channel quality indicator (CQI). On the other hand, the aim of OLLA is to correct reporting inaccuracies and delays. A common approach is to correct the reported CQI based on hybrid automatic repeat request (HARQ) positive and negative acknowledgments sent by the user equipment (UE) [1].

In the literature, most efforts have been focused on the design of robust link adaptation schemes to deal with CQI reporting inaccuracies. In [2], a scheme that takes CQI age into account is proposed for High Speed Downlink Packet Access (HSDPA). In [3], several CQI processing strategies are proposed in HSDPA. In [4], an OLLA scheme that adapts signal quality thresholds based on medium access control (MAC) acknowledgments in IS-856 is proposed. A similar scheme is proposed in [1], which adds an adaptive offset to signal quality measurements to deal with handset measurement and CQI errors, uplink reporting delays and detection errors in LTE. However, few studies have evaluated the problem of OLLA convergence and its impact on the performance of short connections. The analyses presented in [5] and [6] show that link adaptation schemes based on adaptive thresholds may suffer from slow convergence with strongly biased CQI reporting. In [7], it is shown that such a slow convergence is a major issue in current LTE networks due to the prevalence of short connections.

In this letter, a novel self-optimization algorithm for adjusting the initial offset parameter in a classical OLLA scheme for LTE downlink is presented. The proposed algorithm sets the initial offset parameter of all connections to the value obtained at the end of large activity connections, where OLLA has reached steady state and has adapted to the actual channel conditions. As a result, average radio link efficiency and user throughput increase and overall BLER decreases. The proposed algorithm is validated with a connection-level simulator fed with statistics from real connection traces. During the experiments, the proposed algorithm is compared with the case where OLLA parameters are set to the default values suggested by vendors. This letter is organized as follows. Section II presents a theoretical analysis of OLLA imperfections to justify the need for optimizing OLLA parameters. Section III describes the proposed self-optimization algorithm for OLLA. Section IV presents the performance analysis and Section V summarizes the conclusions.

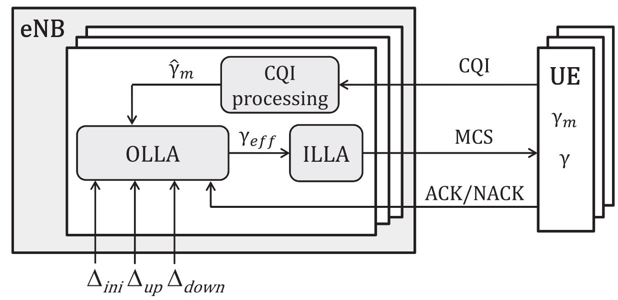

Fig. 1. OLLA block diagram for downlink.

II. Problem formulation

Fig. 1 shows the structure of the classical link adaptation scheme for the downlink [1]. In this scheme, the UE measures downlink signal-to-interference-plus-noise ratio (SINR), γ_m, and sends CQI reports to the base station (eNB) on a per-transmission time interval (TTI) basis. The reported CQI values are processed at the eNB to build an estimate of the measured downlink SINR, $\hat{\gamma}_m$. The SINR measured by the UE differs

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from the real SINR by a systematic (i.e., bias) error term due to imperfections in the SINR measurement unit of the UE, and a random error term due to imperfections in channel estimation [8]. Such a difference can be expressed in logarithmic units as:

$$\gamma_m(k,n) = \gamma(k,n) + \epsilon_s^t(k) + \epsilon_r^t(k,n), \tag{1}$$

where $\gamma_m(k,n)$ and $\gamma(k,n)$ are the measured and real SINR of user (i.e., connection) k in TTI n, and $\epsilon_s^t(k)$ and $\epsilon_r^t(k,n)$ are, respectively, the systematic and random errors introduced by the terminal of user k in TTI n. In (2), dependence on indices k and n shows that the systematic error is constant during a connection, whereas the random error varies with each TTI [9].

At the eNB, the SINR derived from the received CQI is an estimate of the measured SINR used by the UE to compute the CQI value. Estimated and measured SINR differ by a systematic error term, due to differences in the mapping curves used by eNB and UE to derive SINR thresholds for each CQI, and a random error term, due to errors in the CQI feedback channel, the delay in the reporting process and deviations from the assumed channel conditions (e.g., multipath environment, user speed, ...) [8]. Thus,

$$\begin{aligned}\hat{\gamma}_m(k,n) &= \gamma_m(k,n) + \epsilon_s^b(k) + \epsilon_r^b(k,n)\\ &= \gamma(k,n) + \epsilon_s^t(k) + \epsilon_r^t(k,n) + \epsilon_s^b(k) + \epsilon_r^b(k,n)\\ &= \gamma(k,n) + \epsilon_s(k) + \epsilon_r(k,n),\end{aligned} \tag{2}$$

where $\hat{\gamma}_m(k,n)$ is the estimate of $\gamma_m(k,n)$ at the eNB, $\epsilon_s^b(k)$ and $\epsilon_r^b(k,n)$ are, respectively, the systematic and random errors introduced by the eNB for user k in TTI n, and $\epsilon_s(k)$ and $\epsilon_r(k,n)$ are the total systematic and random errors for user k in TTI n. Again, the systematic error introduced by the eNB is fixed, whereas the random error introduced by the eNB varies with each TTI.

The aim of OLLA is to compensate for systematic errors by applying an offset, Δ_{OLLA}, to the estimated SINR to compute an effective (i.e., corrected) SINR as:

$$\gamma_{eff}(k,n) = \hat{\gamma}_m(k,n) - \Delta_{OLLA}(k,n). \tag{3}$$

If $\Delta_{OLLA}(k,n) = \epsilon_s(k)$, then $\gamma_{eff}(k,n)$ is an unbiased estimator of the real downlink SINR experienced by the UE, which can be used by ILLA to select the proper MCS.

From (3), it is deduced that a positive value of Δ_{OLLA} leads to a lower value of γ_{eff}, which translates into a pessimistic interpretation of the reported channel conditions and the selection of a robust MCS. Conversely, a negative value of Δ_{OLLA} leads to a higher γ_{eff}, translating into an optimistic interpretation of the channel conditions and the selection of an aggressive MCS. When Δ_{OLLA} is calculated correctly, γ_{eff} matches the actual channel conditions, systematic errors are compensated and the best MCS is selected.

At the beginning of each radio resource control (RRC) connection, Δ_{OLLA} is initialized to a fixed value, Δ_{ini}, defined on a cell basis. As the connection progresses, Δ_{OLLA} is progressively modified by OLLA based on HARQ feedback. When a positive acknowledgment (ACK) is received, Δ_{OLLA} is decreased by Δ_{down}, and when a negative acknowledgment (NACK) is received, Δ_{OLLA} is increased by Δ_{up}. The ratio $\Delta_{down}/\Delta_{up}$ controls the target BLER that OLLA converges to, given by

$$BLER_T = \frac{1}{1+\frac{\Delta_{up}}{\Delta_{down}}} \approx \frac{\Delta_{down}}{\Delta_{up}}, \quad \text{if } \Delta_{up} \gg \Delta_{down}. \tag{4}$$

Typical values for Δ_{up} and Δ_{down} are 1 dB and 0.1 dB, respectively, to ensure quick recovery from high BLER situations and smooth convergence to equilibrium. These values yield a target BLER of 0.1 (10%).

Note that the target BLER is only reached at the end of large activity connections, for which a large number of ACKs and NACKs are received by the eNB. For these connections, OLLA reaches steady state and Δ_{OLLA} fluctuates around the proper value due to random system errors. In contrast, for small activity connections, convergence is not guaranteed, unless Δ_{OLLA} is properly initialized. When Δ_{ini} is too large, γ_{eff} is initially far below the actual channel conditions. This leads to an excessively conservative selection of the initial MCS and, therefore, user throughput is below the maximum achievable value. Considering a typical value of $\Delta_{down} = 0.1$ dB, OLLA needs at least 10 consecutive successful transmissions (i.e., 10 ms) to compensate for a 1 dB bias in SINR reporting. This is comparable to the average RRC connection activity in current LTE networks [7] and might prevent OLLA from reaching the optimum MCS before the connection is released. On the other hand, when Δ_{ini} is too small, γ_{eff} is far above the actual channel conditions and a too aggressive MCS is initially selected. This causes high BLER figures and unnecessary retransmissions, thus lowering the net user data flow. In both cases, user throughput is negatively affected.

Other link adaptation schemes proposed in the literature improve OLLA convergence speed, but they require changing existing equipment and are thus not directly compatible with currently deployed systems. In the absence of these schemes, a cost-effective solution for legacy networks is to adjust the value of Δ_{ini} properly, as described next.

III. Self-Optimization Algorithm

In this section, an automatic algorithm for optimizing the initial OLLA offset parameter in LTE downlink is described. The motivation of the algorithm is first given and the details are presented later.

A. *Motivation of the Algorithm*

Fig. 2 represents three different realizations of the OLLA process for a sample connection, obtained with a statistical connection-level simulator. The figure shows the evolution of the OLLA offset with three different settings for the initial offset parameter (i.e., $\Delta_{ini} = -10$, 10 and 3 dB). It is observed that, for all settings, the offset converges to the same value (i.e., 3 dB). This was expected since, in the steady state, the offset fluctuates around a fixed value, representing the sum of the bias terms for that specific connection (i.e., $\epsilon_s^t(k) + \epsilon_s^b(k)$). However, when Δ_{OLLA} is initialized to an excessively large value (10 dB), the connection takes longer to reach the steady state, and conservative MCSs are used during the first TTIs of

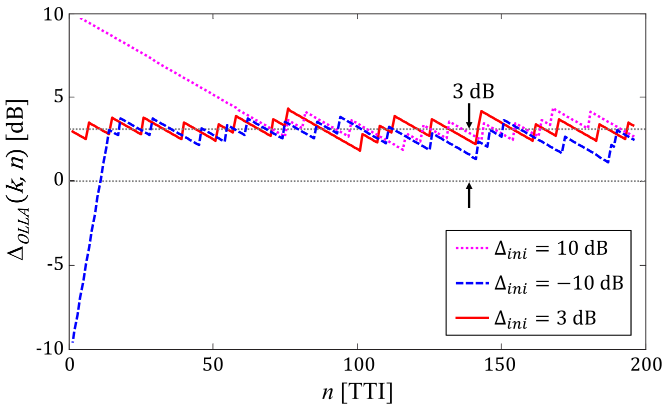

Fig. 2. Realizations of the OLLA process for different values of the initial offset parameter.

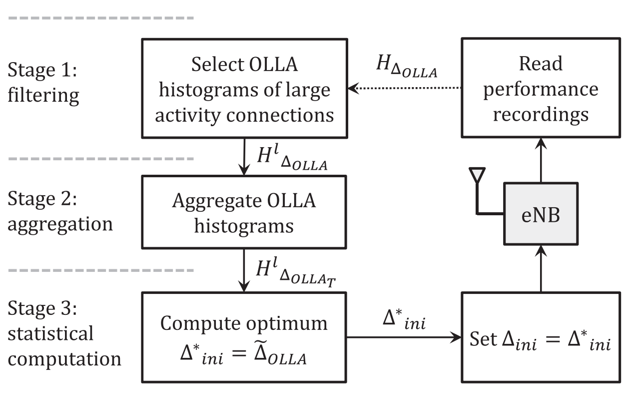

Fig. 3. OLLA self-optimization algorithm flowchart.

the connection. On the contrary, when the initial Δ_{OLLA} is too low (-10 dB), convergence is faster but large BLER figures are experienced in the first TTIs (not shown in the figure). Only when Δ_{OLLA} is initialized correctly (for the considered connection, to 3 dB), selected MCSs are optimum from the beginning of the connection.

More importantly, it can be inferred from the figure that, in large activity connections, the most frequent value of the OLLA offset throughout the connection is close to the bias term for the user. Thus, the bias error term for a large activity connection can be estimated from any central statistic (e.g., the median) of the OLLA offset in that connection. This is not the case for connections with small activity. Nonetheless, it is expected that the bias term in small and large activity connections has the same statistical distribution.

B. Algorithm Outline

Fig. 3 shows the flowchart of the proposed algorithm. The main input to the algorithm is the set of downlink OLLA offset histograms of all the connections completed in a given geographical area and time period. This information is included in performance recordings of connection traces stored in the eNB. The histogram $H_{\Delta_{OLLA}}(k)$ for a connection k consists of N bins, $H_{\Delta_{OLLA}}(k)[i]$, $(i = 1, \ldots, N)$. Each bin contains the number of occurrences of Δ_{OLLA} values between the bin limits, L_{i-1} and L_i. For consistency, $L_0 = -\infty$ and $L_N = \infty$.

The algorithm consists of three stages: filtering, aggregation and statistical computation. In the *filtering* stage, large activity connections are identified. To isolate large activity connections, an internal threshold parameter, A_{th}, is defined as the minimum number of HARQ positive and negative acknowledgment messages (i.e., ACKs + NACKs) to consider a connection as a large activity one. Only histograms for large activity connections are processed in subsequent stages. In the *aggregation* stage, Δ_{OLLA} histograms of large activity connections are aggregated into a single histogram as:

$$H^l_{\Delta_{OLLAT}}[i] = \sum_{k=1}^{N_c} H^l_{\Delta_{OLLA}}(k)[i], \quad i = 1, \ldots, N, \tag{5}$$

where i is the histogram bin index, $H^l_{\Delta_{OLLA}}$ are the Δ_{OLLA} histograms of large activity connections, k is the connection index, and N_c is the number of large activity connections. Finally, in the *statistical computation* stage, the optimized value of the initial offset parameter, Δ^*_{ini}, is computed as the median value of $H^l_{\Delta_{OLLAT}}$, denoted by $\widetilde{\Delta}_{OLLA}$.

The above-described optimization process can be executed periodically to adapt to changing network conditions. Likewise, the algorithm can consider the network as a whole, leading to a single global optimized value, or can be executed on a cell-by-cell basis, providing the best value for each cell.

IV. Performance Analysis

A comparison of the network performance obtained with the default OLLA parameter settings against that obtained with the proposed self-optimizing algorithm is done. The analysis is carried out with a statistical connection-level simulator fed with real connection traces collected from a live LTE network. The aim of the analysis is to show that: a) OLLA convergence is an issue in current LTE networks, and b) tuning Δ_{ini} with the proposed algorithm can improve network performance significantly in a real scenario.

A. Simulation Setup

The analyzed trace dataset consists of 1744890 connections collected during 24 hours in 24 LTE cells in 4 sites selected at random. Cells are distributed in 2 carriers at 734 MHz and 2.132 GHz with 10 MHz and 5 MHz system bandwidth, respectively.

For each connection, trace data includes radio resource control (RRC) connection duration, average user packet data convergence protocol (PDCP) and radio throughput, total occupying time, HARQ activity (i.e., amount of ACKs + NACKs), and CQI and OLLA offset histograms. OLLA histograms contain 8 bins, whose limits are $\{-\infty, -10, -7, -3, -1, 1, 3, 7, +\infty\}$ dB, while CQI histograms contain 16 bins, ranging from CQI 0 to CQI 15.

A statistical connection-level simulator has been developed to analyze the time domain behavior of Δ_{OLLA} and other relevant performance indicators of the connections. The inputs to the simulator are CQI and Δ_{OLLA} cumulative distribution functions, built from traces on a per-connection basis. For each connection, a random CQI is generated on a TTI basis from

TABLE I
NETWORK-LEVEL AND CARRIER-LEVEL SIMULATION RESULTS

Optimization level	Default	Network	Carrier
Δ^*_{ini} [dB]	0	0.991	0.89 (1st), 1.61 (2nd)
Avg. Spectral Efficiency [bps/Hz]	1.906	1.954	1.958
Avg. User Throughput [Mbps]	14.99	15.37	15.41
Avg. Connection BLER [%]	13.94	9.92	9.49

the real CQI distribution. Then, the measured SINR is derived from the CQI value by using link-level mapping curves [10]. The real SINR is computed by adding bias and random error terms, as in (2). For large activity connections (i.e., activity $\geq A_{th} = 1000$), the bias term is obtained from the median value of the OLLA offset histogram of that connection. For small activity connections, the bias term is obtained similarly from a histogram randomly selected from large activity connections. Random errors introduced by the terminal and the eNB are modeled as Gaussian random variables with standard deviation $\sigma_r^t = 1$ dB [9] and $\sigma_r^b = 0.3$ dB [11]. The effective SINR at the eNB is obtained with (3), and MCS is selected based on SINR thresholds for a BLER of 10% derived from link-level simulations [10]. The actual BLER is estimated from the real SINR and the mapping curve corresponding to the selected MCS. Such a BLER value is used to randomly generate ACK or NACK messages, which are then used by OLLA to update the OLLA offset.

Three different OLLA parameter configuration approaches are compared. The first one is the current approach followed by the operator, where Δ_{ini} in downlink is set to 0 dB in all cells of the network. This solution is used for benchmarking purposes. In a second approach, referred to as *network-level optimization*, the optimized value of Δ_{ini} is computed by applying the proposed algorithm to a dataset built by aggregating Δ_{OLLA} statistics in the 24 cells and 24 hours. In a third approach, referred to as *carrier-level optimization*, two values of Δ_{ini} are obtained by applying the proposed algorithm separately to the cells of each carrier.

Method assessment is based on: a) the average spectral efficiency, estimated from the selected MCS and BLER probability [12], b) the average maximum user throughput, computed by multiplying the average spectral efficiency by the system bandwidth of the carrier frequency (5 or 10 MHz), and c) the average connection BLER, computed by mapping the real SINR measurements with link-level simulator curves [10].

B. Analysis Results

Table I summarizes the results of the simulations. First, it is observed that Δ^*_{ini} (i.e., the median of the OLLA offset of large activity connections) calculated on a network or carrier basis is much larger than the default value configured by the operator (0 dB). This is proof of the need for optimizing the initial OLLA offset parameter in the downlink of real networks. From (3), it can be deduced that the positive value of Δ^*_{ini} means that the default configuration is optimistic, leading to an unnecessarily high BLER. Thus, it is anticipated that the main benefit of the optimized settings will be a BLER reduction. Likewise, it is observed that Δ^*_{ini} is significantly different between carriers. It is thus expected that carrier-level optimization should give higher gains than network-level optimization. Specifically, relative BLER reduction is 28.8% (from 13.94 to 9.92%) and 31.9% (from 13.94 to 9.49%) when optimizing at a network- and carrier-level, respectively. At the same time, the relative gain in average spectral efficiency obtained with the proposed algorithm when compared to the current operator approach is 2.52% (from 1.906 to 1.954) and 2.73% (from 1.906 to 1.958) in the network- and carrier-level variants, respectively. Similar gains are obtained for the average maximum user throughput. These results quantify the potential benefit of tuning the initial OLLA offset parameter in the downlink of a real network.

V. CONCLUSION

In this letter, a novel OLLA self-optimization algorithm has been proposed for LTE downlink. By processing connection traces, the algorithm adapts the initial OLLA offset value to the median value observed in large activity connections, where steady state is reached. With the optimized settings, OLLA convergence is faster, leading to increased user throughput and reduced retransmission rates. Such performance benefits are obtained without modifying existing network equipment. The analysis of real connection traces has shown that the optimum value of the initial offset parameter differs significantly from that currently configured by operators. Future work aims at evaluating the benefit of adjusting the initial offset parameter on a daily-, hourly- or a cell-by-cell basis.

REFERENCES

[1] K. Pedersen *et al.*, "Frequency domain scheduling for OFDMA with limited and noisy channel feedback," in *Proc. 66th IEEE Trans. Veh. Technol. Conf.*, 2007, pp. 1792–1796.

[2] A. Muller and T. Chen, "Improving HSDPA link adaptation by considering the age of channel quality feedback information," in *Proc. 62nd IEEE Trans. Veh. Technol. Conf.*, 2005, vol. 3, pp. 1643–1647.

[3] D. Martin-Sacristan, J. Monserrat, D. Calabuig, and N. Cardona, "HSDPA link adaptation improvement based on Node-B CQI processing," in *Proc. Int. Symp. Wireless Commun.*, 2007, pp. 597–601.

[4] D. Paranchych and M. Yavuz, "A method for outer loop rate control in high data rate wireless networks," in *Proc. 56th IEEE Trans. Veh. Technol. Conf.*, 2002, vol. 3, pp. 1701–1705.

[5] H.-J. Su, "On adaptive threshold adjustment with error rate constraints for adaptive modulation and coding systems with hybrid ARQ," in *Proc. 5th Int. Conf. Inf., Commun. Signal Process.*, 2005, pp. 786–790.

[6] K. Aho, O. Alanen, and J. Kaikkonen, "CQI reporting imperfections and their consequences in LTE networks," in *Proc. 10th Int. Conf. Netw.*, 2011, pp. 241–245.

[7] V. Buenestado, J. M. Ruiz-Aviles, M. Toril, S. Luna-Ramirez, and A. Mendo, "Analysis of throughput performance statistics for benchmarking LTE networks," *IEEE Commun. Lett.*, vol. 18, no. 9, pp. 1607–1610, Sep. 2014.

[8] D. Morales-Jimenez, J. J. Sanchez, G. Gomez, M. C. Aguayo-Torres, and J. Entrambasaguas, "Imperfect adaptation in next generation ofdma cellular systems," *J. Internet Eng.*, vol. 3, no. 1, pp. 202–209, 2009.

[9] T. Kolding, F. Frederiksen, and A. Pokhariyal, "Low-bandwidth channel quality indication for OFDMA frequency domain packet scheduling," in *Proc. 3rd Int. Symp. Wireless Commun. Syst.*, 2006, pp. 282–286.

[10] J. Ikuno, M. Wrulich, and M. Rupp, "System level simulation of LTE networks," in *Proc. 71st IEEE VTC*, 2010, pp. 1–5.

[11] M. Ni, X. Xu, and R. Mathar, "A channel feedback model with robust SINR prediction for LTE systems," in *Proc. 7th EuCAP*, 2013, pp. 1866–1870.

[12] "Evolved Universal Terrestrial Radio Access (E-UTRA); Physical layer procedures," 3rd Generation Partnership Project (3GPP), Sophia Antipolis, France, TS 36.213, Sep. 2008.