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Estimating Cell Capacity from Network Measurements in a Multi-Service LTE System

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***Abstract*—In this paper, a method for estimating cell capacity from network measurements in a multi-service Long Term Evolution (LTE) system is presented. Unlike previous work, the proposed method takes into account multiple service-specific constraints, including both delay and throughput constraints. For this purpose, services are first classified by their Quality of Service (QoS) Class Identifier (QCI). Then, several multivariate linear regression equations are used to estimate the value of the different service-specific QoS indicators from network performance statistics collected on a cell basis. The output of the method is the maximum value of a previously selected traffic capacity indicator per cell ensuring that all QoS constraints are fulfilled. Method assessment is based on data taken from a live LTE network. Results show that cell capacity estimation is robust, provided that enough data is available for each service.**

***Index Terms*—LTE, network planning, multi-service, cell capacity**

I. Introduction

Network dimensioning is a critical task in mobile network management. In such a process, operators need to estimate future traffic demand and upcoming network capabilities to detect capacity bottlenecks in advance. Unfortunately, traffic growth and radio capabilities are not easily predictable, causing that operators must be constantly revising their planning forecasts to guarantee an adequate Quality of Service (QoS).

In mobile network dimensioning, estimating the maximum (a.k.a. pole) capacity of the radio access network is a very first step. Cell capacity is defined as the maximum traffic demand for satisfying some QoS constraint. When cell capacity is exceeded, QoS reaches unacceptable levels. Thus, an accurate cell capacity estimate is needed to guarantee an adequate QoS with minimal investment [1]. Estimating cell capacity is simple when a single service is considered. However, estimating cell capacity in a multi-service environment is a challenging task, since not all services demand identical radio resources (e.g., voice call versus videostreaming session) nor share the same QoS criteria (e.g., file transfer versus media streaming). A robust cell capacity estimation method must guarantee that all QoS requirements are fulfilled simultaneously.

In the literature, several theoretical methods have been proposed for determining cell capacity in different radio access technologies, such as Global System for Mobile communications (GSM) [2], Universal Mobile Telecommunications System (UMTS) [2] or Long Term Evolution (LTE) [3]. These analytical approaches rely on simplifying assumptions for mathematical tractability. However, the capacity of a live cell is highly dependent of many factors that are difficult to predict and changing with time and location (e.g., mix of services, terminal capabilities or propagation and mobility conditions). Hence, capacity estimation can only be done properly if all these peculiarities are taken into account. To deal with this diversity, in some studies, cell capacity is estimated by means of simulations. Nonetheless, it is virtually impossible to simulate all possible combinations of the above-mentioned factors. Alternatively, several works have used network performance measurements to improve the accuracy of the capacity estimation process. The benefit of measurement-based approaches is their ability to take the peculiarities of each cell into account. In [4], a dimensioning method based on measurements collected from each network element is proposed for Wideband Code Division Multiple Access (WCDMA) networks. Similarly, a multivariate regression model is proposed in [5] to estimate High-Speed Downlink Packet Access (HSDPA) pole capacity on a cell basis from network performance statistics. However, none of these studies considers multi-service cell capacity estimation for LTE.

In this paper, a novel methodology for estimating cell capacity on a cell basis in a multi-service LTE system from network measurements is proposed. The multi-service nature of LTE traffic is dealt with by classifying services based on their QoS Class Identifiers (QCIs) [6], for which different QoS requirements are defined. In a first step, traffic capacity for each service is estimated by multiple linear regression, similarly to [5]. Such an approach is extended here to consider different QoS constraints for each service. Thus, the focus is put on user performance rather than on network performance. Unlike [5], the proposed method deals with throughput-sensitive and delay-sensitive services. A single cell capacity value is calculated by selecting the most restrictive QoS constraint. Method assessment is based on measurements taken from a live LTE network. Section II outlines the capacity estimation method, Section III presents the results of the proposed method in a live multi-service LTE network and Section IV presents the concluding remarks.

II. Method Description

The aim of the method is to estimate the maximum traffic capacity of each cell in an LTE system under different constraints specific for each QCI traffic flow based on network performance data. Fig. 1 illustrates the flow diagram

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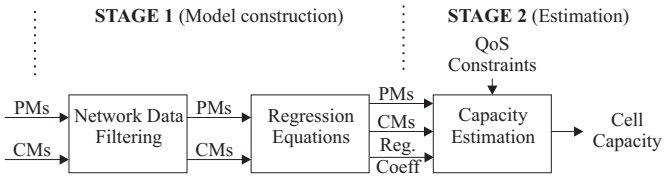

Fig. 1. Flow diagram for cell capacity estimation.

of the process. The inputs to the method are Performance Measurements (PMs) and Configuration Management settings (CMs), stored in the Network Management System (NMS) with a given time resolution. The method consists of two stages. Stage 1 includes data filtering and the construction of regression equations that relate QoS statistics with PMs and CMs network wide. Data filtering aims to select measurement samples that are significant for capacity estimation. For this purpose, only busy hour statistics are selected. The resulting set of equations is then used in Stage 2 to estimate capacity on a cell-by-cell basis given the QoS constraints defined by the operator.

A. Regression equations

The core of the method is the construction of a *Multi-Service Multiple Linear Regression* (MS-MLR) model, consisting of N_{eq} equations (at least, one per QCI class) for estimating the values of a predefined set of service-specific QoS indicators. Each equation in MS-MLR is formulated as

$$p_{QoS}^{(j,l)}(c,h) = \beta_0^{(j,l)} + \sum_{i=1}^{k} \beta_i^{(j,l)} \cdot p_i(c,h) + \epsilon^{(j,l)}(c,h) \qquad (1)$$

where $p_{QoS}^{(j,l)}(c,h)$ is the value of the lth QoS indicator of QCI class j in cell c and hour h, i is used to index variables, $p_i(c,h)$ are the values of PMs and CMs selected a priori as candidate independent variables in cell c and hour h, $\beta_i^{(j,l)}$ is the regression coefficient for each p_i, k is the number of candidate independent variables in the MS-MLR model and $\epsilon^{(j,l)}(c,h)$ is the error term. In the general case, 9 QCI classes are considered (i.e., $j \in \{1,2,\ldots,9\}$) [6].

The regression analysis aims to: a) find the minimal combination of variables for each QCI class j and QoS criterion l that can explain $p_{QoS}^{(j,l)}$ with reasonable accuracy, and b) build an estimate of the regression coefficients, $\beta_i^{(j,l)}$.

A first step is to choose the k candidate independent variables, p_i, for the multi-service regression model. Table I presents PMs and CMs selected as potential independent variables in MS-MLR for all QCIs and QoS criteria (i.e., $\forall j,l$). A large set of predictors is needed because it is difficult to define a priori which variables are the most significant ones. PMs and CMs in Table I are provided by most vendors and prove to be the most relevant ones.

For the regression analysis, a dataset with measurements gathered on a cell and hourly basis is taken from the NMS. From this data, N_{eq} regression equations are built. The variable elimination process described in [5] is used to identify the most relevant variables to predict the value of each QoS indicator

TABLE I
CANDIDATE INDEPENDENT VARIABLES IN MS-MLR MODEL

	Name	Description
Traffic and connection quality indicators	$ActiveUE\_DL$	Avg. no. of simultaneous users per TTI (DL)
	$TrPerc_{QCI}^{(1)}, \ldots, TrPerc_{QCI}^{(9)}$	% traffic for QCI class 1 to 9
	$TH_{QCI}^{(1)}, \ldots, TH_{QCI}^{(9)}$	DL user throughput at Packet Data Convergence Protocol (PDCP) layer for QCI class 1 to 9
	Avg_CQI	Avg. DL Channel Quality Indicator (CQI)
	σ_{CQI}	Standard deviation of CQI distribution
	$CQI\_percent\_5\%$	5%-tile of CQI distribution
	$CQI\_percent\_10\%$	10%-tile of CQI distribution
	$HARQ\_fail\_ratio\_DL$	Hybrid Automatic Repeat Request (HARQ) failure ratio in DL
	$RLC\_retx\_ratio\_DL$	DL Radio Link Control (RLC) retransmission ratio in Acknowledged Mode
	$PDCCH\_ack\_ratio$	Ratio of correct resource assignments in Physical DL control channel (PDCCH)
	$VoLTESatisfUsRatio$	Ratio of Voice over LTE (VoLTE) calls whose delay in 99% of UL packets is below certain budget
Cell config.	BW	LTE system bandwidth
	CFI_mode	Control Format Indicator (CFI) configuration
	$PUCCH\_SR\_users$	Max. no. of users allowed to send Scheduling Request (SR) in UL
	$PUCCH\_CQI\_users$	Max. no. of users allowed to report CQI in UL

$p_{QoS}^{(j,l)}$. For each QCI class j and QoS indicator l in that QCI class, an equation is first built with all the k variables. Then, an iterative process starts where the least significant variable is eliminated in each iteration. The least significant variable is that with the largest P-value statistic [7]. After each iteration, a simpler (but less accurate) regression model is built with one less variable. The simplifying process ends when the accuracy of the estimation falls below a certain threshold. In this work, goodness of fit is measured by the determination coefficient, R^2 [7], and the stop criterion is that $R^2 < 0.7$. Statistics in the regression analysis are collected network wide, and the simplified equation is therefore valid for all cells.

B. Cell capacity estimation

Once N_{eq} simplified equations have been constructed, cell capacity is estimated. With this purpose, one capacity variable, denoted as p_{i_0}, is chosen from the set of independent variables in the equations. Then, the value of p_{i_0} in each cell c is computed by solving (1) for p_i (in this case, $i = i_0$), as

$$\bar{p}_{i_0}^{(j,l)}(c) = \frac{p_{QoS,target}^{(j,l)} - \hat{\beta}_0^{(j,l)} - \sum_{i=1, i\neq i_0}^{k'(j,l)} \hat{\beta}_i^{(j,l)} \cdot \bar{p}_i(c)}{\hat{\beta}_{i_0}^{(j,l)}} \quad , \qquad (2)$$

where $p_{QoS,target}^{(j,l)}$ is the target value for the lth QoS indicator in QCI class j, defined by the operator, $\hat{\beta}_i^{(j,l)}$ are the estimates of regression coefficients obtained from the network-wide analysis, $k'(j,l)$ is the number of independent variables in each simplified equation, and $\bar{p}_i(c)$ is the average of all hourly measurements for indicator i in cell c. By applying (2), a value of cell capacity, $\bar{p}_{i_0}^{(j,l)}(c)$, is obtained for each QCI class j and QoS criterion l in every cell c. Finally, cell capacity, CC, is calculated as

$$CC(c) = \min_{(j,l)} \left(\bar{p}_{i_0}^{(j,l)}(c) \right) \quad . \qquad (3)$$

The *min*(•) operator ensures that all QoS target values, $p_{QoS,target}^{(j,l)}$, are fulfilled if CC is not exceeded. Note that the value of CC is obtained from network measurements collected

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on an hourly basis. Thus, the dependency on factors such a specific user locations and rapid fluctuations of inter-cell interference is averaged out.

III. Method Assessment

A. Analysis Set-up

Network performance and configuration data was collected in a live LTE network. The analyzed area comprises 656 cells in a populated area. Two carriers at 700 MHz and 2100 MHz are used with 10 and 5 MHz system bandwidth (BW), respectively. Base stations in the area have 2 transmit antennas and possible Transmission Modes (TM) are TM 0 (Single transmit antenna) and TM 2 (Open loop spatial multiplexing with cyclic delay diversity). Network measurements were collected on an hourly and cell basis for 6 days, resulting in $24 \cdot 6 \cdot 656 = 94464$ samples in the dataset. To obtain reliable estimates, the analysis is restricted to samples for the busy hour of every cell (i.e., one sample per cell and day).

In the considered network, only three QCI classes were configured by the operator: QCI 1 for Voice over LTE (VoLTE), QCI 5 for IP Multimedia Subsystem (IMS) signaling and QCI 8 for TCP-based data services. Network traffic with QCI 5 was negligible compared to that of the other QCIs (i.e., 0.02% versus 2.68% and 97.30% for QCI 1 and 8, respectively). Although VoLTE traffic was also small, analysis is carried out for QCI 1 and 8 to illustrate the multi-service feature of the proposed capacity estimation approach (i.e., $j \in \{1, 8\}$). For the robustness of capacity estimations, data samples with no VoLTE connection are discarded. As a result, only 2222 samples are used to derive regression equations.

The selected QoS performance indicators are: a) $VoLTESatisfUsRatio$ for QCI 1, as a delay-sensitive service, and b) $TH^{(8)}_{QCI}$ for QCI 8, as a throughput-sensitive service (i.e., $p^{(1)}_{QoS}$=$VoLTESatisfUsRatio$ and $p^{(8)}_{QoS}$=$TH^{(8)}_{QCI}$). The maximum delay budget defined by the operator for $VoLTESatisfUsRatio$ is 80 ms. Thus, one only QoS criterion is used per QCI class (i.e., N_{eq}=2).

In all data samples, CFI_mode, $PUCCH\_SR\_users$ and $PUCCH\_CQI\_users$ have fixed values network wide. The same is true for other important cell parameters, such as antenna configuration or MIMO transmission modes. Thus, these variables are not significant for the regression equations, and they are excluded as candidate variables. The remaining 11 independent variables in Table I are selected as candidate predictors for the regression equations (i.e., k=11). Table II presents statistics for the selected PMs measured on a cell and hourly basis. Note that traffic percentages segregated by QCI, $TrPerc^{(1)}_{QCI}$ and $TrPerc^{(8)}_{QCI}$, are used in both regression equations as independent variables, showing that service performance is affected by PMs from other services (e.g., VoLTE delay is affected by the number of data users). The wide range of values observed in the table is clear evidence of the different network conditions, which is the origin of the need for estimating cell capacity on a per-cell basis.

Two regression models are compared: the Full Model (FM), with 11 independent variables, and a Simplified Model (SM), with minimal number of variables for an acceptable fit. In the comparison, the determination coefficient, R^2, is used as a figure of merit.

TABLE II
Network performance statistics

	Min	Average	Max	Std
Independent variables, p_i				
$ActiveUE\_DL$	0.0038	0.47	8.3	0.57
$TrPerc^{(1)}_{QCI}$ [%]	0	2.68	87.26	5.88
$TrPerc^{(8)}_{QCI}$ [%]	12.56	97.30	100	5.9
Avg_CQI	5.81	8.84	14.73	1.41
σ_{CQI}	0.294	0.98	3.13	0.24
$CQI\_percent\_5\%$	1.44	4.11	12.54	1.15
$CQI\_percent\_10\%$	2.01	4.91	13.56	1.28
$HARQ\_fail\_ratio\_DL$ [%]	1.9	6.35	13.97	1
$RLC\_retx\_ratio\_DL$ [%]	0	6.2e-2	3.26	0.11
$PDCCH\_ack\_ratio$ [%]	27.7	97.26	99.75	3.93
BW [MHz]	5	-	10	-
QoS performance indicators, $p^{(j)}_{QoS}$				
$VoLTESatisfUsRatio$ [%]	0	91.77	100	24.33
$TH^{(8)}_{QCI}$ [Mbps]	1.28	10.93	47.33	4.99

TABLE III
Results for full model

Regression Statistic				
Determination coefficient	$R^{2(1)}$=0.09		$R^{2(8)}$=0.755	
Model analysis				
	$\hat{\beta}^{(1)}_i$	$P^{(1)}$	$\hat{\beta}^{(8)}_i$	$P^{(8)}$
$Constant$ (β_0)	-1160	0.003	-83.2	0.05
$ActiveUE\_DL$	-2.83	0.004	-2.61	1.6e-118
$TrPerc^{(1)}_{QCI}$[%]	11.1	0.005	0.57	0.18
$TrPerc^{(8)}_{QCI}$[%]	11	0.005	0.56	0.19
Avg_CQI	4.96	0.01	2.53	5e-33
σ_{CQI}	-13.2	3e-4	-1.53	1.3e-4
$CQI\_percent\_5\%$	-1.5	0.7	-0.9	0.04
$CQI\_percent\_10\%$	-3.17	0.49	1.46	3.5e-3
$HARQ\_fail\_ratio\_DL$ [%]	-1.45	0.03	-1.12	9e-52
$RLC\_retx\_ratio\_DL$ [%]	10	0.04	0.056	0.91
$PDCCH\_ack\_ratio$ [%]	1.56	6e-30	0.08	2.4e-8
BW [MHz]	3.57e-5	0.93	1.6e-3	6e-260

B. Analysis Results

Table III shows FM parameters. Regression coefficients and P values in the table correspond to the estimation of $VoLTESatisfUsRatio$ and $TH^{(8)}_{QCI}$ for QCI 1 and 8, respectively. R^2 value is also indicated for both estimations. It is observed that BW and $TrPerc^{(8)}_{QCI}$ have the highest P-values in FM for QCI 1 and 8, respectively. These variables are thus selected as the first variable to be discarded for the SM.

Based on the R^2 values in Table III ($R^{2(1)} = 0.09$ and ($R^{2(8)} = 0.755$), it is deduced that FM predicts $TH^{(8)}_{QCI}$ accurately, but fails to predict $VoLTESatisfUsRatio$. A closer analysis shows that this is due to the low VoLTE traffic in the available dataset, which proved to be less than 0.24 VoLTE connections per cell and hour on average. As a result, $VoLTESatisfUsRatio$ measurements are not statistically robust, but are rather sensitive to the specific VoLTE user(s) connected to a cell in one hour.

To support the previous statement, a reduced dataset is built only with samples including 3 or more VoLTE connections. A new FM is constructed with additional independent variables broken down by QCI class (specifically, UpLink (UL)/

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TABLE IV
RESULTS FOR SIMPLIFIED MODEL

Regression Statistic				
Determination coefficient	$R^{2(1)}$=0.08		$R^{2(8)}$=0.73	
Model analysis				
	$\hat{\beta}_i^{(1)}$	$P^{(1)}$	$\hat{\beta}_i^{(8)}$	$P^{(8)}$
$Constant$ (β_0)	-68.81	5e-8	-18.82	1.2e-51
$ActiveUE\_DL$	-2.62	4.4e-3	-2.43	2e-107
$TrPerc_{QCI}^{(1)}$ [%]	0.105	0.22	–	–
Avg_CQI	1.045	0.004	2.92	6e-273
$HARQ\_fail\_ratio\_DL$ [%]	–	–	-1.26	7e-67
$PDCCH\_ack\_ratio$ [%]	1.57	7e-33	–	–
BW [MHz]	–	–	1.5e-3	1e-236

DownLink (DL) PDCP packet loss ratio and Physical Resource Block utilization). In this new FM, $VoLTESatisfUsRatio$ is estimated with a higher R^2 (=0.4). More importantly, the lowest P-values (i.e., highest relevance) are obtained for newly added QCI 1 specific variables, supporting the idea that, with such a low network traffic, $VoLTESatisfUsRatio$ estimation is given by the performance of individual connections (and not by global network behavior).

Interestingly, in Table III, BW has the highest and lowest P-values for QCI 1 and 8, respectively. Obviously, the higher the system BW, the better throughput performance for data services, which is the reason for the low P-value of BW in QCI 8 equation. However, QCI 1 traffic is prioritized by LTE schedulers, causing that these services are less sensitive to the share of radio resources (i.e., BW availability), and hence the higher P-value of BW for QCI 1 regression equation.

The FM equations in Table III are simplified by eliminating variables progressively based on their P-value. Table IV shows SM parameters. For QCI 1, the final SM model has 4 variables as a trade-off between model complexity and accuracy. It is observed again that SM performs poorly for estimating $VoLTESatisfUsRatio$ (R^2=0.08). In contrast, estimation of $TH_{QCI}^{(8)}$ has similar R^2 than in FM ($R^2 = 0.73$ compared to 0.755 in FM). All variables have P-value close to 0, which points out the need for considering all variables. A closer inspection of the selected variables shows that $TH_{QCI}^{(8)}$ decreases with $ActiveUE\_DL$ and $HARQ\_fail\_ratio\_DL$, and increases with Avg_CQI and BW. $VoLTESatisfUsRatio$ decreases with $ActiveUE\_DL$, and increases with Avg_CQI, $PDCCH\_ack\_ratio$ and $TrPerc_{QCI}^{(1)}$.

C. Cell capacity estimation

Once SM is available, cell capacity can be estimated on a cell basis. $ActiveUE\_DL$ indicator is chosen as the capacity indicator (i.e., $p_{i_0}^{(j)}$=$ActiveUE\_DL^{(j)}$). Note that $ActiveUE\_DL$ is the aggregation of active users for all services. Target values for QoS indicators are $p_{QoS,target}^{(1)} \equiv VoLTESatisfUsRatio = 90\%$ and $p_{QoS,target}^{(8)} \equiv TH_{QCI}^{(8)} = 5$ Mbps. By using (2), $\overline{ActiveUE\_DL}^{(j)}(c)$ is estimated for each QCI class j and cell c.

Fig. 2 compares the probability distribution of $\overline{ActiveUE\_DL}^{(1)}(c)$ and $\overline{ActiveUE\_DL}^{(8)}(c)$. In the figure, it is observed that $\overline{ActiveUE\_DL}^{(1)}(c)$ tends to be lower than $\overline{ActiveUE\_DL}^{(8)}(c)$. Thus, the QoS criterion of QCI 1 traffic is more restrictive than that of QCI 8 traffic. Specifically, the average cell capacity to ensure the QoS criterion of QCI 8 in this network is 3.02 DL active users per Transmission Time Interval (TTI), whereas only 1.13 users per TTI are possible for QCI 1. Such a low value is consistent with network performance measurements shown in the third column of Table II, where $VoLTESatisfUsRatio = 91.77\%$ for 0.47 users per TTI on average. It should be pointed out that cell capacity estimates for QCI 1 are not robust due to low VoLTE traffic in the considered dataset. This result has also been observed in other datasets from other operators, for all of which VoLTE is still in an early stage of development.

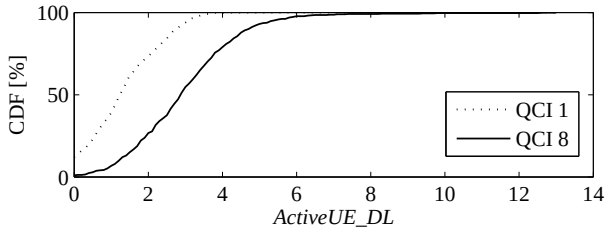

Fig. 2. Probability distribution of the average number of $ActiveUE\_DL$.

IV. CONCLUSION

In this paper, a measurement-based method to estimate LTE cell capacity on a cell basis under multi-service QoS constraints has been proposed. The core of the method is the construction of several multi-variate linear regression equations based on PMs collected on a cell and hourly basis in the NMS. Unlike analytical approaches, the proposed statistical method has a low computational load, which makes it ideal for automatic network planning tools. The presented regression analysis on data taken from a live LTE network has shown a strong correlation between QoS performance and the average number of active users in the downlink, average CQI, system BW and ratio of successful assignments in PDCCH. With the available dataset, regression models have shown reasonable accuracy for services with QCI 8, but poor accuracy for services with QCI 1 (i.e., VoLTE). This is expected to be solved as VoLTE traffic increases in the near future.

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