QoS and network performance estimation in heterogeneous cellular networks validated by real-field measurements

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ABSTRACT
Mobile network operators observe a significant disparity of quality of service (QoS) and network performance metrics, such as the mean user throughput, the mean number of users and the cell load, over different network base stations. The principal reason being the fact that real networks are never perfectly hexagonal, base stations are subject to different radio conditions, and may have different engineering parameters. We propose a model that takes into account these network irregularities in a probabilistic manner, in particular assuming Poisson spatial location of base stations, log-normal shadowing and random transmission powers. Performance of base stations is modeled by spatial processor sharing queues, which are made dependent of each other via a system of load equations. In order to validate our approach, we estimate all the model parameters from the data collected in a commercial network, solve it and compare the spatial variability of the QoS and performance metrics in the model to the real network performance metrics. Considering two scenarios: downtown of a big city and a mid-size city, we show that our model predicts well the network performance.

Categories and Subject Descriptors
C.2.1 [**Network architecture and design**]: Wireless communication; G.3 [**Probability and Statistics**]: Queueing theory,Stochastic processes; D.2.8 [**Software Engineering**]: Metrics—*performance measures*; I.6 [**Simulation and modeling**]: Types of simulation—*Monte Carlo*

General Terms
Algorithms,Measurements,Performance,Theory

Keywords
Heterogeneous wireless cellular networks, cell load, Poisson, QoS, measurements, HSDPA, LTE

1. INTRODUCTION
Real, commercial cellular networks are never perfectly regular. First of all, the geometry of base stations (BS) is usually far from being perfectly hexagonal, because of various constraints that operators have in deploying their networks, e.g. unavailability of desired locations, targeting traffic hot spots, etc. Irregularity of the spatial pattern of BS is usually more pronounced in dense urban environments. Further, physical irregularity of the urban environment (shadowing) additionally induces variable radio conditions for different base stations. Finally, base stations are located at different heights, may have different radiation patterns and use different transmission powers. Such heterogeneity of a cellular network implies a spatial disparity of base station performance metrics and *QoS (Quality of Service) parameters* observed by users in different cells of the network. For example, it has been observed that the mean user throughput varies a lot across different base stations, with no clear, apparent dependence on the traffic demand; cf Figure 1 (for throughput units we use kbps or equivalently kbit/s).

The aforementioned spatial disparity of the performance metrics represents a challenge for the network operators, in particular in the context of the network dimensioning. It is very important for network operators to be able to estimate this disparity, i.e. to have models that can predict the spatial distribution of QoS characteristics in function of the traffic demand at different BS, that is usually well estimated (measured in the deployed network or predicted via marketing studies). In this paper we propose a model allowing for such an analysis and validate it by comparing the results it gives to real field measurements.

The principal reason of difference in the performance of different BS lies in the fact that they serve zones (cells) of different sizes, which is an immediate consequence of the irregular BS positioning. Moreover, these BS/cells are interdependent in their performance. Indeed, the extra-cell interference makes the user throughput in a given cell depend on the "activity" of other cells in the network. Our model, considered in this paper, takes into account the variable size of network cells, different transmitted powers and captures the cell inter-dependence via a system of load equations.

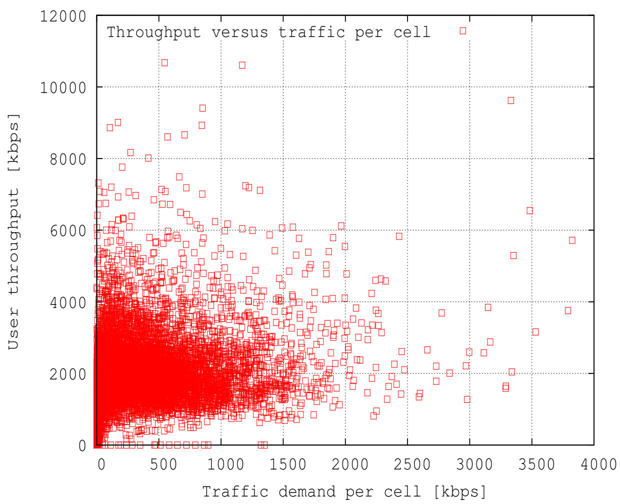

Figure 1: Mean user throughput in function of the traffic demand. Points represent measurement done by different BS in an operational network, during 24 different hours of some given day.

Our model takes into consideration the single user link capacity to express users' maximal bit-rates that depend on users' radio conditions and traffic demand due to resource sharing. Users dynamics (arrivals and departures) is captured using queueing theory and permits to establish the relation between the traffic demand and users' QoS metrics. We obtain and solve the system of load equations and in such manner obtain the cell loads of all cells in the considered network. The other two QoS parameters, mean number of users and mean user throughput per base station, can be expressed as functions of cell load for a considered cell. As a final goal we compare the CDF (cumulative distribution function) of QoS parameters obtained by our model and real-field measurements and check the good concordance between CDFs.

We validate our model against real field measurements performed in a commercial network in two different cites in Europe. More precisely, we take as the model input the densities of BS in these networks, the spatial distribution of the power emitted by the BS and the average traffic demand, and calculate the spatial distribution of the cell load, the number of users per BS and the mean user throughput. We show that the obtained results match the real field measurements.

In the present work we focus on spatial pattern of BS and power variations between different BS. Our goal is to build a simple model that is able to predict the spatial variability of the QoS metrics observed by real-field measurements in commercial networks. We are particularly interested in the distributions of the following QoS and network parameters: *cell (base station) load, mean number of users per base station and mean user throughput per base station* and we build a model that produces CDF of the aforementioned QoS parameters. This work is a continuation of our work in [2]. There, we built a model based on stochastic geometry and Palm probability formalism to estimate the spatial mean of above mentioned QoS parameters over a given area comprising certain number of base stations. The main result of [2] is that we showed how to calculate the mean user throughput in function of traffic demand. We demonstrated that the mean user throughput over a given network is equal to the ratio of the traffic demand and number of users over the whole network. Note that such a mean is not equivalent to the arithmetic average of mean user throughput over all cells in the considered network. In [2] we assumed constant BS power, while here we consider the heterogeneous networks and we derive the distribution of QoS parameters and not only their mean values.

In both [2] and the present work we validate our approach by comparison to real-field measurements.The importance of such comparison is also evoked in [14], where the authors use very similar approach to model the *dependence* between the intercell interference and traffic demand, which is a corner stone of our approach. The model is developed considering the orthogonal users' channels which is the case in LTE (Long Term Evolution) networks and also HSDPA (High Speed Downlink Shared Channel) networks from which we gathered the measurements which makes the comparison between our model and real-field measurements relevant.

1.1 Related work

The disparity of cell load and QoS parameters has already been observed in the literature. For example [18] shows temporal and spatial cell load fluctuations in cellular commercial networks. These results are obtained from data collected by the mobile operators. In [13], traffic and cell load disparity are shown graphically. Data are derived from nationwide 3G cellular network and the results are presented from network and user point of view. In [7] the authors analyzed QoS (throughput etc.) perceived by the users using data collected from mobile operators and experiments. QoS parameters such as throughput, latency etc. are also analyzed based on field-measurements in [15]. Cell load and QoS parameters disparity are assumed in many works treating load balancing. Load balancing consists in the redistribution of load between cells in such way that all cells are equally loaded. Namely, the articles as [12], [6], [17] and [19] present different algorithms for spectrum and energy efficient load balancing. The performance of heterogeneous networks gained a lot of research interest recently, for example see [4] and [8], since their deployment is already commercial and will probably continue to grow. In [11] the authors give an algorithm for network planning implying cell load disparity such that to compensate spatially non-uniform traffic demand, but they don't give the CDF of cell load and other QoS parameters.

The authors of [9] and [14] describe the dependence between the traffic demand and the interference in wireless cellular networks and show that there is a fixed-point problem in the expressions giving the cell load. These two works give a basis for the work in [2] that we further develop here.

1.2 Paper organization

We present the model in Section 2. The spatial pattern used for modelling base stations' positions is presented. Then the expressions of the SINR (signal-to-interference-and-noise-ratio) and peak bit-rate are given. Further, we define the traffic demand and the service policy.

Section 3 presents a semi-analytic method method that permits to predict the disparity of QoS parameters between the different cells of a wireless cellular network. We present the expressions of the QoS metrics: *cell load, mean number of users and mean user throughput*. Then we explain the interdependence between base stations (cells) in a network and give a mathematical formulation of this dependence.

In Section 4 we present a numerical setup for the model previously explained and produce concrete numerical examples. We also give a justification for the spatial pattern of base stations' positions. Morever, we explain the real-field measurements and compare our model to them. Section 5 concludes the paper.

2. MODEL DESCRIPTION

In this section, we present a simulation method that permits to predict the disparity of QoS parameters between the different cells of a wireless cellular network. To do so, we give firstly an expression of the propagation loss between a base staion and a user taking into account the shadowing and variable base stations' powers. Then we give the expressions for SINR and users peak bit-rates considering a realistic network scenario for HSDPA and LTE technologies. In particular, we account for the fact that the base stations that are idling, i.e., have no users to serve, do not contribute to the interference. Consequently the loads of the different cells are interdependent and we shall end this section by characterizing this dependence through a system of cell load equations.

2.1 Shadowing, power and BS pattern

We consider a cellular network comprising base stations whose locations $X_1, X_2, \ldots \in \mathbb{R}^2$ are modeled by a homogeneous Poisson point process of intensity parameter $\lambda \in \mathbb{R}_+^*$ over a disc of radius D and denoted by $\Phi = \sum_{n\in\mathbb{N}^*} \delta_{X_n}$ where δ_x is the Dirac measure at $x \in \mathbb{R}^2$. Each BS X_n is characterized by a transmitting power $P_n \in \mathbb{R}_+^*$. We shall assume that $P_1, P_2, \ldots$ are *i.i.d.* (independent and identically distributed) *marks* of the point process Φ (i.e., given Φ, the transmitting powers $P_1, P_2, \ldots$ are i.i.d. random variable with some fixed distribution).

The propagation loss due to *distance* between base station X_n and a user located at $y \in \mathbb{R}^2$ is $\ell(y - X_n)$ where the function ℓ is given by

$$\ell(x) = (K\,|x|)^{\beta}, \quad x \in \mathbb{R}^2 \tag{1}$$

where $K > 0$ and $\beta > 2$ are given constants. *Shadowing* is a supplementary propagation loss induced by the eventual obstacles between the transmitter and the receiver. The shadowing between a given base station X_n and all locations $y \in \mathbb{R}^2$ is modeled by some random field $\{\mathbf{S}_n(y - X_n)\}_{y\in\mathbb{R}^2}$. We assume that the random fields $\mathbf{S}_1(\cdot), \mathbf{S}_2(\cdot), \ldots$ are i.i.d marks of Φ.. In general, we do not need to assume any particular distribution for $\mathbf{S}_1(\cdot)$ (neither independence nor the same distribution of $\mathbf{S}_1(y)$ across $y \in \mathbb{R}^2$). The shadowing random fields $\{\mathbf{S}_n(\cdot)\}_{n\in\mathbb{N}^*}$ and the transmitting powers $\{P_n\}_{n\in\mathbb{N}^*}$ are assumed independent.

The received power at location $y \in \mathbb{R}^2$ from BS X_n equals

$$L_n^{-1}(y) = \frac{P_n \mathbf{S}_n(y - X_n)}{\ell(y - X_n)}, \quad n \in \mathbb{N}^* \tag{2}$$

We assume that each base station serves the zone where its signal is the strongest one:

$$V(X_n) = \left\{ y \in \mathbb{R}^2 : L_n(y) \le \min_{k\in\mathbb{N}^*\setminus\{n\}} L_k(y) \right\} \tag{3}$$

called *cell* of X_n, where $L_n(y)$ is the inverse of the received power given in Equation (2).

2.2 SINR and peak bit-rate

In HSDPA and LTE networks a given base station transmits only if it has at least one user to serve. Taking this fact into account in an exact way requires to multiply the power received from each interfering BS by the indicators that it is not idling. This, in consequence, would lead to the probabilistic dependence of the service process at different cells and result in a non-tractable model. For this reason, we take into account whether an interfering BS X_k is idling or not in a simpler way, multiplying its powers P_k by the *probability* $p(X_k)$ that it is not idle in the steady state of users' arrivals and departures.Thus the SINR equals

$$\mathrm{SINR}(y, \Phi) = \frac{L_n^{-1}(y)}{N + \sum_{k\in\mathbb{N}^*\setminus\{n\}} p(X_k) L_k^{-1}(y)} \tag{4}$$

for every $y \in V(X_n)$, where N is the noise power. The above expression doesn't comprise intra-cell interference since users within the same cell are assigned *orthogonal channels* either in time (in HSDPA) or frequency (in LTE).

REMARK 1. Pilot channel. *Indeed, when BS X_k is idle, it still emits the pilot channel whose power is assumed to be a fixed fraction $\epsilon \in [0, 1]$ of the total power P_k. Thus $p(X_k)$ in (4) should be replaced by $p(X_k)(1 - \epsilon) + \epsilon$.*

The *peak bit-rate* at location y, is defined as the bit-rate of a user located at y if he was alone in the cell. We assume that the peak bit-rate is some function $R(\mathrm{SINR})$, of the SINR. For example in the case of MIMO (Multiple Input Multiple Output) antennas, this function has the following form [16, Equation (3.169)]

$$R(\mathrm{SINR}) = bW\mathbf{E}\left[\log_2\left[\det\left(I + \mathrm{SINR} HH^*\right)\right]\right]$$

where I is identity matrix, W is the frequency bandwidth, b is a correction factor accounting for a practical performance of wireless channel, H is a random matrix representing fading, and $\mathbf{E}[\cdot]$ is the mathematical expectation with respect to fading. In the particular case of SISO (Single Input Single Output) channel, we have

$$R(\mathrm{SINR}) = bW\mathbf{E}\left[\log_2\left(1 + \mathrm{SINR}\,|H|^2\right)\right] \tag{5}$$

where H is the fading random variable.

2.3 Traffic demand and service policy

We shall consider variable bit-rate (VBR) traffic; i.e. users arrive to the network and require to transmit some volume of data at a bit-rate decided by the network. Each user arrives at a location uniformly distributed and requires to download a random volume of data of mean $1/\mu$ bits. The duration between the arrivals of two successive users in each geographic zone S of surface $|S|$ is an exponential random variable of parameter $\gamma \times |S|$. This means that on average there are γ arrivals per surface unit and per time unit. The arrival locations, inter-arrival durations as well as the data volumes are assumed independent.

We assume that the users don't move considerably during their calls. Each user stays in the system for the time necessary to download his data. This takes a random (service) time because the bit-rate with which he is served depends on the configuration of other users *served by the same base station*. Users depart from the system immediately after having downloaded their data.

The traffic demand per surface unit (traffic demand density) is then equal to $\rho = \frac{\gamma}{\mu}$ which may be expressed in bit/s/km^2. The traffic demand for BS X_n equals

$$\rho\left(X_n\right) = \rho\left|V\left(X_n\right)\right|, \quad n \in \mathbb{N}^* \tag{6}$$

where $|V(X_n)|$ is the surface of area of the cell $V(X_n)$.

We shall assume that each user in a cell gets an equal portion of time for his service. Thus when there are k users in a cell, each one gets in the long term a bit-rate equal to his peak bit-rate divided by k. More explicitly, if a base station located at X serves k users located at $y_1, y_2, \ldots, y_k \in V(X)$ then the bit-rate of the user located at y_j equals $\frac{1}{k} R\left(\mathrm{SINR}\left(y_j, \Phi\right)\right)$, $j \in \{1, 2, \ldots, k\}$.

3. SEMI-ANALYTIC METHOD

We present in the present section a semi-analytic method that permits to predict the disparity of QoS parameters between the different cells of a wireless cellular network.

3.1 Quality of service

For a fixed configuration of BS Φ, the service of users arriving to the cell $V(X_n)$ of a given BS $X_n \in \Phi$ can be modeled by an appropriate (spatial) multi-class processor sharing queue, with classes corresponding to different peak bit-rates characterized by user locations $y \in V(X_n)$. Note also that a consequence of our model assumptions, the service processes of different queues are independent.

Consider the stationary state of these queues in the long run of the call arrivals and departures. Using queuing theory tools, it is proved in [9, Proposition 1] that:

- Each base station X_n can serve the traffic demand within its cell if this latter doesn't exceed some *critical* value which is the harmonic mean of the peak bit-rates over the cell; that is

$$\rho_{\mathrm{c}}\left(X_n\right) := \left|V\left(X_n\right)\right| \left[\int_{V(X_n)} R^{-1}\left(\mathrm{SINR}\left(y, \Phi\right)\right) dy\right]^{-1} \tag{7}$$

- The mean user throughput in the cell equals

$$r\left(X_n\right) = \max(\rho_{\mathrm{c}}\left(X_n\right) - \rho\left(X_n\right), 0) \tag{8}$$

- The mean number of users in the cell equals

$$N\left(X_n\right) = \frac{\rho\left(X_n\right)}{r\left(X_n\right)} \tag{9}$$

- Moreover, we define the *cell load* as

$$\theta\left(X_n\right) = \frac{\rho\left(X_n\right)}{\rho_{\mathrm{c}}\left(X_n\right)} \tag{10}$$

- The probability that BS X_n is not idle in the steady state (has at least one user to serve) equals

$$p\left(X_n\right) = \min\left(\theta\left(X_n\right), 1\right) \tag{11}$$

Note that the probability $p(X_k)$ for each interfering BS X_k appears in the expression (4) of the SINR.

3.2 Dependence between cells

Using Equations (10) and (7) respectively, we deduce that the cell load of BS X_n equals

$$\begin{aligned}
&\theta\left(X_n\right) \\
&= \frac{\rho\left(X_n\right)}{\rho_{\mathrm{c}}\left(X_n\right)} \\
&= \rho \int_{V(X_n)} R^{-1}\left(\mathrm{SINR}\left(y, \Phi\right)\right) dy \\
&= \rho \int_{V(X_n)} R^{-1}\left(\frac{L_n^{-1}(y)}{N + \sum_{k \neq n} p(X_k) L_k^{-1}(y)}\right) dy \\
&= \rho \int_{V(X_n)} R^{-1}\left(\frac{L_n^{-1}(y)}{N + \sum_{k \neq n} \min\left(\theta\left(X_k\right), 1\right) L_k^{-1}(y)}\right) dy
\end{aligned} \tag{12}$$

Note here again that the the load of each BS depends on the loads of all other BS in the network. Thus, we obtain a system of equations with the loads $\{\theta(X_n)\}_{n \in \mathbb{N}^*}$ as unknowns which we call system of *cell-load equations*. From the result presented in [14] we can conclude the uniqueness of the solution of (12) with $\theta(X_n) < 1$, $(\forall n \in \mathbb{N}^*)$ i.e. if such a solution exist then it is unique. Note also that the loads which are equal or greater than one indicate unstable cells.

On the other hand, we can express the mean number of users (9) and the mean user throughput (8) in each cell as function of its load and traffic demand

$$N\left(X_n\right) = \left[\max\left(\frac{1}{\theta\left(X_n\right)} - 1, 0\right)\right]^{-1}, \quad r\left(X_n\right) = \frac{\rho\left(X_n\right)}{N\left(X_n\right)} \tag{13}$$

Consequently, we may calculate the network performance by solving firstly the system of cell-load equations (12) and then deducing the number of users and user throughput in each cell using the above expressions. We shall compare the empirical distributions of the cells' characteristics obtained in this way to the real-field measurements in the numerical section 4.

3.3 Discrete users' positions

We generate users' positions over the network as a homogeneous Poisson point process of density 30λ and approximate the integral in (12) by the corresponding discrete sum. The shadowing random variables for the different user positions are gerenerated as i.i.d. log-normal random variables with *logarithmic-standard deviation* σ_S (expressed in dB). Note that the auxiliary users' point process permits not only to evaluate numerically the integral in (12), but also permits to account for spatial correlation of shadowing; the mean spatial decorrelation distance being the average distance between two user locations.

3.4 Constant power model

In order to evaluate the effect of the variability of the BS powers, we shall compare the results of the above model with a model where all the BS emit the same power. In this latter, all the BS emit the power

$$\tilde{P}_n = E\left[P_1\right], \quad n \in \mathbb{N}^*$$

and the shadowing equals

$$\tilde{\mathbf{S}}_n(y - X_n) = \frac{P_n \mathbf{S}_n\left(y - X_n\right)}{E\left[P_n\right]}, \quad n \in \mathbb{N}^* \tag{14}$$

so that the received power (2) remains as the original model.

4. NUMERICAL RESULTS

In this section we compare the numerical results of the semi-analytic method proposed in Section 3 to the *real-field measurements*. Specifically, we compare the CDF of cell load, mean number of users and mean user throughput of the different base stations at a given hour in a operational HSDPA network (within two different cities) to the results of the proposed method. More precisely, we use MATLAB to solve the system of equations given by (12) over the whole network, and obtain the cell loads for all cells in the network. The mean number of users and user throughput are then deduced using Equation (13).

4.1 Real-field measurements

Now, we describe the real-field measurements. The raw data are collected using a specialized tool which is used by operational engineers for network maintenance. This tool measures several parameters for every base station 24 hours a day. In particular, one can get the cell load, traffic demand, number of users, mean user throughput for each cell in each hour. We have also the BS coordinates which permit to estimate the intensity λ of BS per unit surface.

We choose one hour during the day and estimate the corresponding empirical CDF of the QoS parameters.

4.2 Numerical setup for simulation

We generate a Poisson process of BS with intensity λ over a disc of radius

$$D = 10\sqrt{\frac{1}{\pi\lambda}}$$

The distance coefficient in (1) equals $K = 7117\text{km}^{-1}$, the path loss exponent $\beta = 3.8$. The shadowing standard deviation equals $\sigma_S = 8$dB. The frequency bandwidth equals

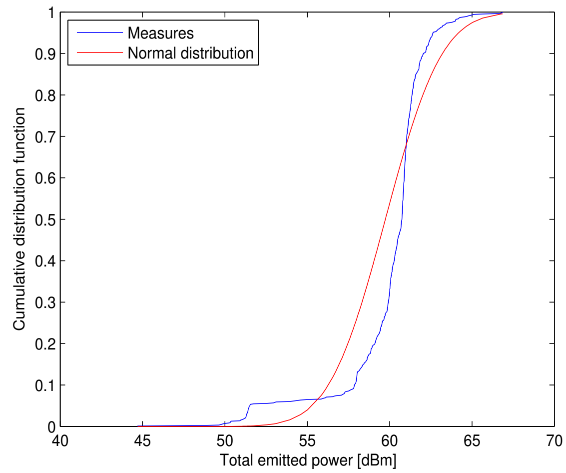

Figure 2: CDF of BS powers in the operational network in the downtown of a big city (blue) and normal distribution approximation (red).

$W = 5$MHz and the noise power is $N = -96$dBm. We take $b = 0.3$ in the peak bit-rate expression (5) for HSDPA. We consider three-sectorial antennas with azimuths π, $\pi + 2\pi/3$ and $\pi - 2\pi/3$ and antenna pattern described in [1, Table A.2.1.1-2].

We assume that the transmitting power P_n has a log-normal distribution of logarithmic-standard deviation σ_P. In order to justify this model, we give the empirical CDF of transmitting powers in dB estimated from measurements in the operational network on Figure 2. This figure shows that this CDF may be approximated by a normal distribution with standard deviation $\sigma_P = 5.3$dB. The mean transmitting power of each BS including a global antenna gain equals $E\left[P_n\right] = 60$dBm. A 10% fraction of this power is used by the pilot channel; cf Remark 1.

In the constant power model described in Section 3.4, each BS emits a constant power $\tilde{P}_n = 60$dBm and the shadowing (14) has a log-normal distribution of standard deviation

$$\sigma_{\tilde{S}} = \sqrt{\sigma_S^2 + \sigma_P^2} \simeq 9.6\text{dB}$$

4.3 Poisson network hypothesis

Regarding spatial pattern of BS, we use Poisson model. The idea of using Poisson process to model cellular network already exist in the literature, see for example [10]. Moreover, it is shown in [3] that starting from any deterministic pattern of BS (including the regular Hexagonal one), when the shadowing variance becomes sufficiently high, the radio parameters (such as the propagation loss with the serving base station) converge to those of a Poisson model. This is a reasonable assumption, especially for urban environment and/or indoor position of receiver. Second, deployed network don't follow a regular spatial pattern, especially not those in urban and suburban environments, so the mentioned convergence is faster. For example, in some urban areas in Europe, the geographical pattern of base stations

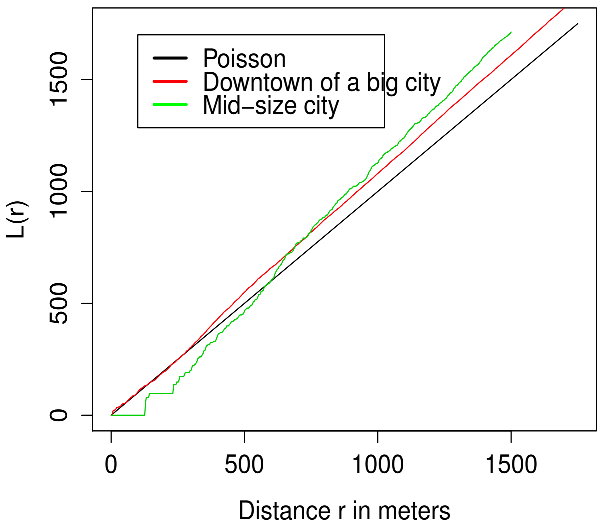

Figure 3: Ripley's L-function of two patterns of base stations which are nearly Poissonian. Note that mid-size city exhibits more irregularity than the downtown of a big city.

is nearly Poissonian which is checked in Figure 3 using Ripley's L-function $L(r) = \sqrt{K(r)/\pi}$, where $K(r)$ is Ripley's K-function [5].

The other sources of irregularities, as for example non-uniform traffic demand, are not considered in the present work. Consequently, we will consider networks or parts of a network where we can assume uniform spatial traffic demand (e.g. downtown of a big city or a typical rural area).

4.4 Results

Figures 4, 5 and 6 show the spatial distribution (across different cells) of the cell load, mean number of users per cell and the mean user throughput in the network deployed in the downtown of a big city. Recall that these metrics represent, themselves, the steady-state (averaged over time) performance characteristics of individual cells. Analogous characteristics regarding the network in a mid-size city are presented on Figures 7, 8 and 9. Tables 1 and 2 show means and standard deviations of these spatial distributions.

All figures and tables present the distributions estimates in our model as well as the real-field measurements. For seek of comparison, we present also on the figures the results obtained in the model described in Section 3.4 where the emitted powers are assumed constant. The simulation curves represent the means over ten repeated network simulations, with the horizontal bars giving the standard deviation of this averaging. In what follows we discuss the presented results in more details.

The estimated network density and the traffic demand in

Table 1: Downtown of a big city

MEASURES	mean	standard deviation
cell load	0.1854	0.1337
mean number of users	0.2608	0.2511
mean user throughput[kbit/s]	2135	698
SIMULATIONS	mean	standard deviation
cell load	0.1845	0.1059
mean number of users	0.2531	0.2147
mean user throughput[kbit/s]	2054	425

Table 2: Mid-size city

MEASURES	mean	standard deviation
cell load	0.1190	0.1035
mean number of users	0.1530	0.1734
mean user throughput[kbit/s]	1975	733
SIMULATIONS	mean	standard deviation
cell load	0.1321	0.0937
mean number of users	0.1774	0.2861
mean user throughput[kbit/s]	2051	601

the downtown of a big city are, respectively, $\lambda = 4.62\text{km}^{-2}$ and $\rho = 483$kbit/s/cell. Analogous values for the mid-size city are $\lambda = 1.27\text{km}^{-2}$ and $\rho = 284$kbit/s/cell. Note that in the latter scenario the traffic demand is smaller, but the network is less dense and also less regular (cf Figure 3). We use these values as input parameters for our model.

In general we see a good agreement between real field measures and the model analysis with randomized emitted power. Under the constant power assumption the model predicts well the median of the cell load and the mean number of users but fails to match the spatial distribution of these characteristics. Clearly, the spatial variability of power creates more spatial heterogeneity of these characteristics in the network. Regarding the mean user throughput the constant power assumption fails to predict even the median. Extensions of the model, e.g. letting it account for further sources of disparity in the deployed networks (e.g. different heights of antennas) could perhaps improve the quality of prediction.

5. CONCLUSION

In this work we propose a model allowing one to estimate the distributions of QoS and network parameters in wireless cellular networks with orthogonal users' channels. The model is based on a queuing-theoretic evaluation of the performance of individual cells and a static network simulation, allowing one to capture the inter-cell dependence. We compare the results obtained using this model with real-field measurements demonstrating a good prediction of the performance of real networks. We believe our model can be useful in network performance estimation and dimensioning.

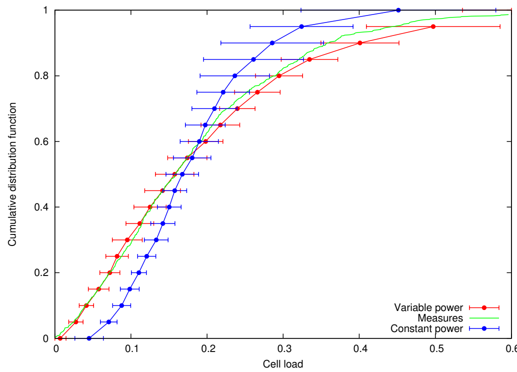

Figure 4: CDF of cell load for the downtown of a big city obtained either from the variable power model, from real-field measurements, or from the model where the emitted powers are assumed constant.

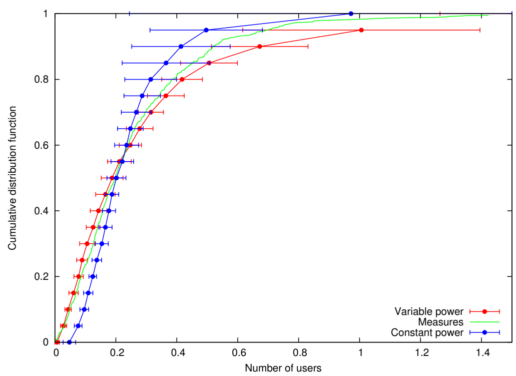

Figure 5: CDF of the mean number of users for the downtown of a big city.

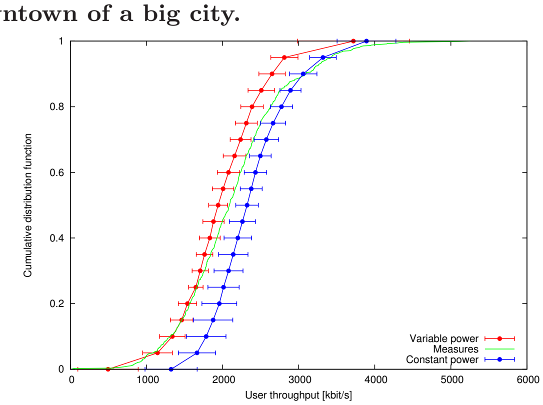

Figure 6: CDF of the throughput for the downtown of a big city.

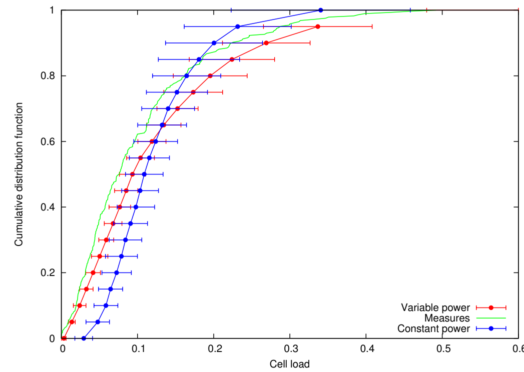

Figure 7: CDF of cell load for mid-size city obtained either from the variable power model, from real-field measurements, or from the model where the emitted powers are assumed constant.

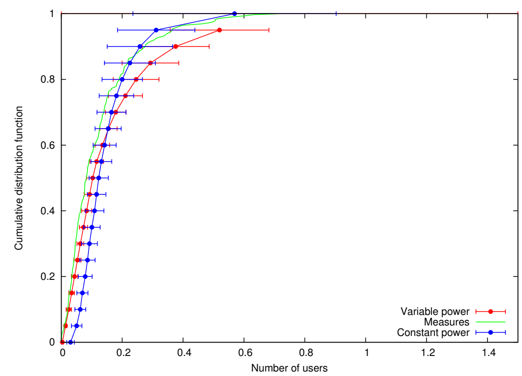

Figure 8: CDF of the mean number of users for the mid-size city.

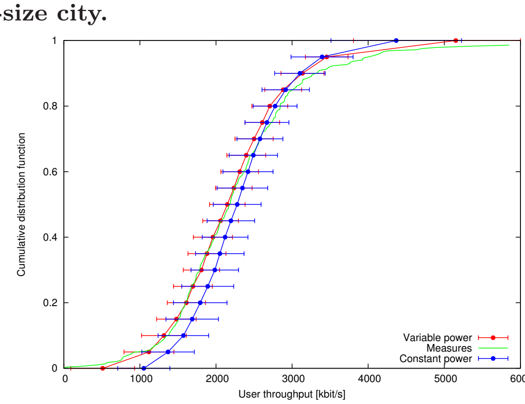

Figure 9: CDF of the throughput for the mid-size city.

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