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Models for the downlink capacity of WCDMA systems with dedicated channels as specified in the UMTS Release '99 rely on the orthogonality factor for approximating the intra-cell interference due to multi-path propagation. This model is no longer applicable for the HSDPA as the performance of fast scheduling and adaptive modulation and coding depends on the small-scale fading effects. This leads to the problem on how to produce reliable statistics for the long-term system-level behavior when small-scale fading effects are not negligible. In this paper we introduce a general framework on how to perform time-efficient simulations that capture the effects of small-scale fading.

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1 Introduction

Mobile network operators continue to deploy the High Speed Downlink Packet Access (HSDPA) service in their existing UMTS networks. From the users perspective, the HSDPA offers high bit rates (promised are up to 14.4 Mbps) and low latency. From operators perspective, the HSDPA is hoped to play a key role for the much longed for break through of high quality mobile data services. From a technical perspective, the HSDPA brings a new paradigm to UMTS: Instead of adapting transmit power to the radio channel condition in order to ensure constant link quality, HSDPA adapts the link quality to the radio channel conditions. This enables a more efficient use of scarce resources like transmit power, code resources and also hardware resources.

In the literature, a wide range of publications on several aspects of the HSDPA exists. The capacity of the HSDPA, mostly in terms of throughput, is the focus of many works which use simulations to obtain their results. The models in early publications like [1] and [2] concentrate on aspects of scheduling, HARQ and physical layer techniques. In [3], link-layer simulations have been performed which are used to fit the signal-to-noise ratio to CQIs. All these models do not consider the impact of coexistent dedicated channels on the HSDPA. This is done in [4], which assumes a fixed number of OVSF codes reserved for the HS-DSCH in their extensive simulation. The impact of the HSDPA on network planning is the focus of [5], [6], [7] and [8]. All these works use simulations for their results. The impact of code restraints is considered in [5] and [6], while [7] and [8] concentrate on the influence of the multi-path model and scheduling. In [9], a method for the estimation of the interference for the HSPDA is proposed.

Evaluating the performance of HSDPA arises the problem that the system behavior essentially depends on variations on a very small time scale. This makes detailed simulations on the one hand necessary but on the other hand extremely time consuming such that traffic dynamics that might appear on much larger time scales can not be simulated. The typical solution is to apply the results from link-layer simulations e.g. CQI traces [3] or even a location dependent bandwidth [7, 8] to system-level simulation. The problem in doing so is that the traces are in general not location specific and furthermore do not consider system variations like changes of the other-cell interference.

The key problem in high-level time-dynamic simulations is how to determine the amount of data that HSDPA users transmit in a certain period of time where we assume constant shadowing and constant transmit powers of all NodeBs, i.e. during a preriod of time where the system remains constant. After that period the users might move to new locations, new users might appear and some users might leave the system according to the data they transmitted. Then, the data volume transmitted in the next time period can be determined for the new situation. We provide a simple and computationally efficient algorithm to estimate the distribution of the CQI (Channel Quality Identifier) in a static network situation. The CQI distribution allows to determine the bandwidth of the HSDPA users under consideration of the available codes and the UE classes for different scheduling disciplines. In this paper we focus on the simplest one, round-robin scheduling.

The rest of the paper is organized as follows: In Section 2 we very briefly summarize the key features of HSDPA. In Section 3 we present our model for approximating the HSDPA bandwidth. In Section 4 we demonstrate the accuracy of our algorithm. In Section 5 we summarize the main contributions of this paper and describe the next steps in generalizing the model.

2 Short Description of HSDPA functionality

The main features of the HSDPA are AMC (adaptive modulation and coding), packet-scheduling with time and code-multiplex, Hybrid ARQ, and short TTIs (Transmission Time Interval) of 2ms. AMC and opportunistic scheduling are enabled by a feedback channel that is used by the mobiles to report their CQI (Channel Quality Identifier) to the NodeB. The TFRC (Transport Format and Resource Combination) relates the CQI to the TBS (Transport Block Size, volume trnasmitted per TTI), the number of parallel codes, and the reference power adjustment. In [10] TFRCs for different UE classes are specified. Indirectly, the TRFCs also define coding rate and modulation scheme. Accordingly, a mobile has to estimate its channel quality and map it to the right CQI. In general this is a quite complicated task as a certain channel prediction is necessary to compensate for the feedback delay. In [3] a formula for mapping the SIR to the CQI is proposed:

$$CQI = \max(0, \min(30, \lfloor SIR/1.02 + 16.62 \rfloor \tag{1}$$

Opportunistic scheduling allows the NodeB to consider the CQIs reported from different mobiles in the scheduling, see e.g. [11] for different scheduling schemes. Hybrid ARQ enables a secure communication with rather low SIR values by soft-combining retransmissions with prior transmissions. According to [3] the first transmission aims at a FER of 10%.

3 Bandwidth Approximation

In the following we describe an algorithm to approximate the HSDPA bandwidth in a static network situation. The network consists of a set of NodeBs $\mathcal{B}$ and every NodeB y transmits with power T_y. We focus on the set $\mathcal{M}_x$ of HSDPA mobiles served by NodeB x. NodeB x spends power $T_{x,h}$ for the HSDPA and may use up to $C_{x,h}$ codes in parallel.

The propagation channel from NodeB x to mobile k consists of a set $\mathcal{P}_{x,k}$ of paths p with associated average relative received power m_{β_p} and delay τ_p, as e.g. defined by the 3gpp [12] for evaluating the HSDPA performance. The average relative received powers are normalized, i.e. their sum equals one. Furthermore, let $d_{x,k}$ be the average propagation gain from NodeB x to mobile k. Then, the power $R_{x,k,p}$ mobile k receives on path p is

$$R_{x,k,p} = T_x \cdot d_{x,k} \cdot \beta_p \tag{2}$$

where β_p is a random variable for the instantaneous relative propagation loss of multi-path component p. If every multi-path component experiences independent Rayleigh fading, β_p is exponentially distributed with mean m_{β_p}. Assuming that the Rake receiver has a finger on every multipath component and uses perfect Maximal Ratio Combining, the HSDPA achieves a SIR of

$$\gamma_k = \tfrac{T_{x,h}}{T_x} \cdot \sum\nolimits_{f \in \mathcal{P}_{x,k}} \frac{\beta_f}{\left(\sum\nolimits_{y \in \mathcal{B} \setminus x} \frac{T_y \cdot d_{y,k}}{T_x \cdot d_{x,k}} \cdot B_{y,k} \right) + B_{x,k,f}} \tag{3}$$

$$\text{with } B_{y,k} = \sum\nolimits_{p \in \mathcal{P}_{y,k}} \beta_p \text{ and } B_{x,k,f} = \sum\nolimits_{p \in \mathcal{P}_{x,k} \setminus f} \beta_p.$$

In Eq. (3) every finger experiences the same other-cell interference as we assume slowly varying channel conditions. Thermal noise is neglected since in well-designed networks, it is by magnitudes less than the multiple access interference.

Let us introduce the variable $\Delta_x = T_{x,h}/T_x$ for the ratio of HSDPA power to total cell power, and the variable γ_k for the SIR achieved by the total cell power, i.e.

$$\gamma_{k,h} = \Delta_x \cdot \gamma_k. \tag{4}$$

For the rest of this paper, we refer to the variable γ_k as the normalized SIR (nSIR), and to the variable Δ_x as the HSDPA power ratio (PR) .

The TBS is limited by the reported CQI and the available codes at the cell. We obtain the mean TBS for mobile k in a random TTI as

$$E[TBS_k] = \sum_{q=0}^{30} p_k(q) \cdot min\Big(TBS(q), TBS^*(C_{h,k})\Big), \tag{5}$$

where $p_k(q)$ is the probability that mobile k reports CQI q and $TBS^*(C_{h,k})$ is the maximum TBS supported by the available HSDPA codes. With round robin scheduling, a user transmits in every nth TTI where $n = \mathcal{M}_x$ is the number of HSDPA mobiles. Then, the average bandwidth B_k of a user k is

$$B_k = \tfrac{E[TBS_k]}{n \cdot 2ms \cdot (1+p_{err})} \tag{6}$$

where p_{err} is the probability of an erroneous transmission in the first stage of the hybrid ARQ process. Further retransmissions occur with low probability such that their impact on the bandwidth is negligible for this rather coarse bandwidth approximation. If we observe a certain period of time consisting of T TTIs the average transmitted data volume is $\mathrm{E}\left[V_k\right] = B_k \cdot T \cdot 2ms$.

The key of our bandwidth approximation is an algorithm to determine the distribution of the CQI in a random TTI with independent powers for the individual paths. The knowledge of the CQI distribution allows the computation of the average bandwidth for other scheduling disciplines like proportional fair scheduling or MaxCQI scheduling, as well. Furthermore, the volume transmitted in a certain period of time is actually a random variable with a variance that strongly depends on the autocorrelation of the reported CQI. However, further scheduling disciplines and the CQI auto-correlation are outside the main focus of this paper.

The distribution of the CQI follows from the distribution function of γ since the PR Δ means only an offset in the decibel scale. A direct calculation of the distribution function of γ, or even of its the mean is numerically intractable. Accordingly, our approach is to estimate the type of distribution and approximate the mean and standard deviation. Therefore, we assume that mean and variance of γ are functions of the ratio Σ of average other-cell received power to average own-cell received power

$$\Sigma_k = \sum\nolimits_{y \in \mathcal{B} \setminus x} \sigma_{k,y} \text{ with } \sigma_{k,y} = (T_y \cdot d_{y,k})/(T_x \cdot d_{x,k}) \tag{7}$$

for which we introduce the abbreviation APR. This is of course an approximation since exactly, γ depends not only on Σ_k but on the received power ratio $\sigma_{k,y}$ of every non-serving NodeB. The assumption that $\mathrm{E}[\gamma]$ is a function of Σ_k is also the basis of the orthogonality factor model

$$\mathrm{E}[\gamma_k] = \tfrac{1}{\Sigma_k + \alpha} \tag{8}$$

where the orthogonality factor α assumes values between 0.05 and 0.4 according to the multi-path profile. The orthogonality factor model is well accepted and introduced in many textbooks on UMTS radio network planning. In fact, most work concerning analytical models or higher layer UMTS simulations rely on the orthogonality factor model. However, for studying the performance of HSDPA, the orthogonality factor is not appropriate, since computing the CQI distribution requires the distribution of the SIR.

Unlike the orthogonality factor model, we are interested in the nSIR in decibel scale and in the functions $f_E(\Sigma)$ and $f_{STD}(\Sigma)$ that map the APR Σ to the mean $\mathrm{E}[\gamma]$ and the standard deviation $\mathrm{STD}[\gamma]$ of nSIR in decibel scale. We propose to use four-parametric Weibull functions

$$f_{a,b,c,d}(x) = a - b \cdot e^{-c \cdot x^d} \tag{9}$$

both for f_E and f_{STD}.

Let us now assume that we know the distribution of γ in decibel scale. Then, the mean and standard deviation allow us to determine the parameters of the function such that we also obtain the distribution function $a_\Sigma(t)$ for a certain APR Σ.

Applying Eq. (1) that relates SIR to CQI we obtain the following CQI distribution:

$$p_{CQI}(q) = \begin{cases} a_\Sigma\left(\phi_u(q)\right) & \text{for } q = 0 \\ a_\Sigma\left(\phi_u(q)\right) & \\ \quad -a_\Sigma\left(\phi_\ell(q)\right) & \text{for } q = 1, ..., 29 \\ 1 - a_\Sigma\left(\phi_\ell(q)\right) & \text{for } q = 30 \end{cases} \tag{10}$$

where the functions $\phi_u(q)$ and $\phi_\ell(q)$ relate CQI q to the respective maximum and minimum normalized SIR for a certain HSDPA power ratio. The functions are given as

$$\begin{aligned} \phi_u(q) &= (q - 15.62) \cdot 1.02 + \Delta_{x,h}[dB] \\ \phi_\ell(q) &= (q - 16.62) \cdot 1.02 + \Delta_{x,h}[dB]. \end{aligned} \tag{11}$$

Finally, the mean TBS follows from Eq. (5) considering the available codes and the UE class, and Eq. (6) translates the mean TBS to the mobiles' bandwidth with round robin scheduling.

4 Parameterization and Validation

In this section we will identify parameters for the functions $f_E(\Sigma)$ and $f_{STD}(\Sigma)$ and investigate to what extent we can speak of functions. Furthermore, we investigate which distribution matches best with the normalized SIR.

4.0.1 Simulation Model

At this place we want to demonstrate the idea and accuracy of our model using a two level Monte Carlo simulation. In the first level we generate 5000 different static network situations. A static network situation corresponds to a set of NodeB locations, the power of the NodeBs, and the location of a single mobile. We assign the mobile to the closest NodeB and determine the APR Σ. In the second level we generate 5000 snapshots of the multi-path profile, i.e. values for β_p, for every static situation which allows us to determine the mean, the standard deviation, and a histogram of the normalized SIR.

For evaluating the quality of our model in the most general way, we generated the set of NodeBs according to a homogeneous Poisson process within an area of $5km \times 5km$ and with a density of 1.27 NodeBs per km^2. The NodeB power is chosen uniformly between 4W and 10W. The mobile is located randomly within an inner area of $3km \times 3km$. The average propagation gain is derived from the distance $dist_{y,k}$ between NodeB and mobile according to the COST231 model

$$d_{y,k}[dB] = -140.9 - 36.4 \cdot \log_{10}(dist_{y,k}). \tag{12}$$

We consider the three multi-path profiles defined in [12] for HSDPA conformance testing, ITU Pedestrian A (PA), ITU Pedestrian B (PB), and ITU Vehicular A (VA). The gains β_p^* of the single multi-paths p normalized to a maximum path gain of 0dB are summarized in Tab. 1.

4.0.2 Parameters for the Weibull functions

The parameters for the functions $f_E(\Sigma)$ and $f_{Std}(\Sigma)$ are found for the three multipath profiles by fitting the Weibull functions to the means and standard deviations obtained by the simulation. The parameters and the corresponding root mean square error (rmse) are summarized in Tab. 2.

Figs. 1 and 2 show the mean and the standard deviation of the normalized SIR versus the APR Σ. The dots represent the values obtained from the simulation, the solid lines show the fitted curves. Note that in Fig. 1 the x-axis is scaled logarithmically in the left half and linearly in the right half.

The main observations are first, that the mean and the standard deviation are not exactly functions of Σ, second, that the means are much more function-like than the standard deviation, and third, that the fitted curves match the middle of the occurring values quite well. Furthermore, we observe that PA with a single dominating path achieves by far larger mean SIRs than PB and VA but the standard deviation is also larger. Quite remarkably, the standard deviation of PA is almost independent of Σ while the mean varies from +9dB to -9dB.

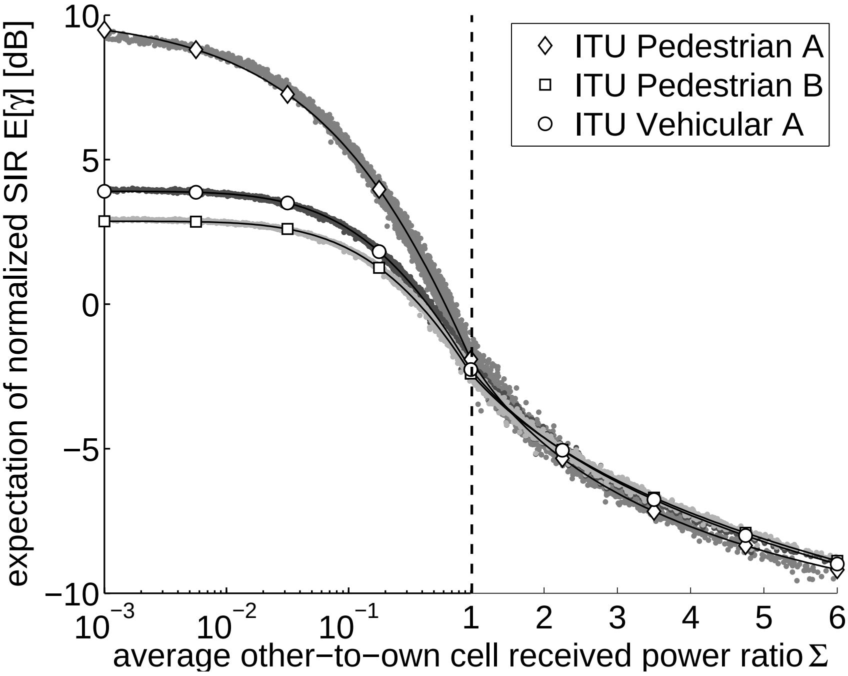


Figure 1: Fitting of $f_E(\Sigma)$ by Weibull functions

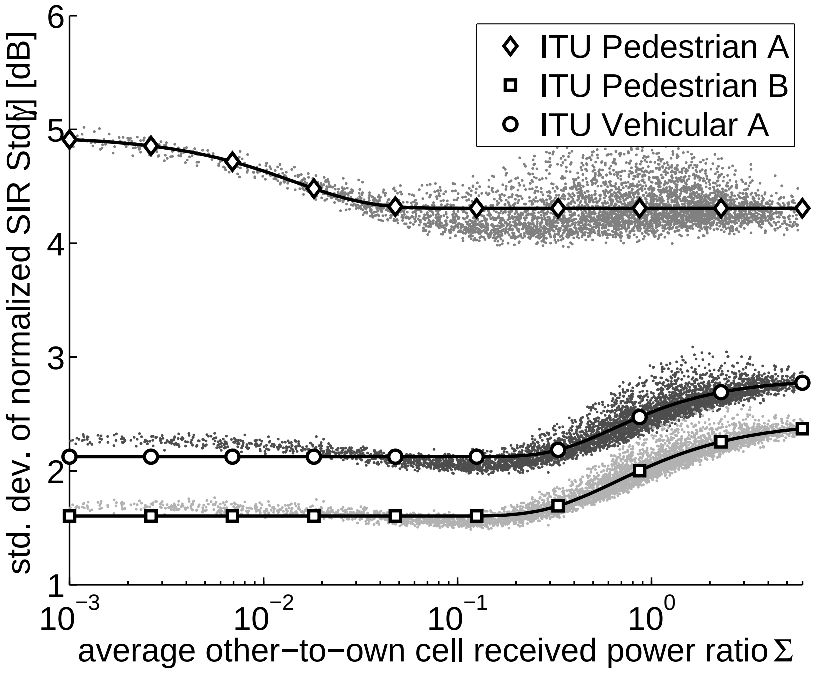


Figure 2: Fitting of $f_{STD}(\Sigma)$ by Weibull functions

	β^*_{p1}	β^*_{p2}	β^*_{p3}	β^*_{p4}	β^*_{p5}	β^*_{p6}
PA	0	-9.7	-19.2	-22.8	-	-
PB	0	-0.9	-4.9	-7.8	-8	-23.9
VA	0	-1	-9	-10	-15	-20

Table 1: Multi-path fading profiles.

	$f_E(\Sigma)$			$f_{STD}(\Sigma)$		
	PA	PB	VA	PA	PB	VA
a	9.23	2.87	3.90	4.31	1.60	2.12
b	53.63	51.42	51.06	-0.63	-0.83	-0.68
c	1.57	2.28	2.11	117.06	0.63	0.56
d	-0.22	-0.24	-0.24	1.12	-1.14	-1.32
rmse	0.21	0.07	0.08	0.17	0.07	0.09

Table 2: Parameters for the Weibull model

4.0.3 Distribution of the normalized SIR

The next step is to find a distribution that approximates the distribution of γ, preferably for all multi-path profiles and the whole range of APRs. In order to compare fitted distribution and sample distribution we compute the probabilities $p_{sim}(i,j)$ and $p_{est}(i,j)$ that γ falls in the interval

$$I(i) = \begin{cases} (-\infty; -16.62] & \text{for } i = 0 \\ (-16.62 + (i-1; i]) \cdot 1.02 & \text{for } 1 \leq i \leq 40 \\ (24.18; \infty) & \text{for } i = 41 \end{cases}$$

where j denotes the situation with jth smallest value of Σ, i.e. the jth point from the left in the previous figures. Then, we group J situations together and define the maximum SSE of the kth group as

$$MaxSSE(k) = \max_{j \in \{1,\ldots,100\}} SSE(k \cdot J + j)$$
$$\text{with } SSE(j) = \sum_{i=0}^{41} \left(p_{sim}(i,j) - p_{est}(i,j)\right)^2.$$

We consider four distributions in decibel and in linear scale: Normal, Lognormal, Inverse Gaussian, and Gamma. In decibel scale we further distinguish the distribution defined by the sample mean and standard deviation (opt) and the distribution defined by the mean and standard deviation obtained from the Weibull model (fit). Fig. 4 depicts the obtained maximum SSE for the three multi-path profiles. The markers are not drawn at specific values. Their only function is to improve the clarity of the figure.

From the figures we conclude that there is no distribution that is optimal for the whole range of multi-path profiles and APRs. The best distribution over the whole range is the Normal distribution in decibel scale with maximum SSEs of about 0.08 for PB and $\Sigma < 0.1$. An Alternative to using a single distribution for the whole range of APRs is to apply different distributions to different APR ranges. For $\Sigma > 0.1$ the Normal distribution in decibel scale or the Lognormal/Inverse Gaussian distribution in linear scale are good candidates. For $\Sigma < 0.1$ the Lognormal, Inverse Gaussian, or Gamma distribution in decibel scale provide quite low SSEs for all three multi-path profiles.

For further investigation, we compare the sample mean TBS with the estimated mean TBS. Fig. 3 shows this comparison for the three multi-path profiles with 15 Codes, UE class 4, and $T_{x,h} = T_x$. Additionally, the mean TBS for PA with only 10 and 3 codes are shown. Please note, that all these values and also the network layouts are chosen artificially with the only purpose of demonstrating the accuracy of the model. The difference between Lognormal, Inverse Gaussian, and Gamma distribution for $\Sigma < 0.1$ is not significant. The Normal distribution matches best for PA with 15 codes, but slightly underestimates for VA. For $\Sigma > 0.1$ the Normal distribution leads to quite accurate results in all cases. As a result we propose either to use only the Normal distribution in decibel scale, or additionally to use the Lognormal distribution in decibel scale for $\Sigma < 0.1$. The decision for Lognormal instead of Inverse Gaussian or Gamma is the simpler computation of its distribution function. An alternative would be to use a single sample distribution for $\Sigma < 0.01$ since the other-cell interference becomes negligible.

5 Conclusion

We presented a method to determine the bandwidth of an HSDPA user in a static network simulation which means that only small-scale fading effects occur. The key

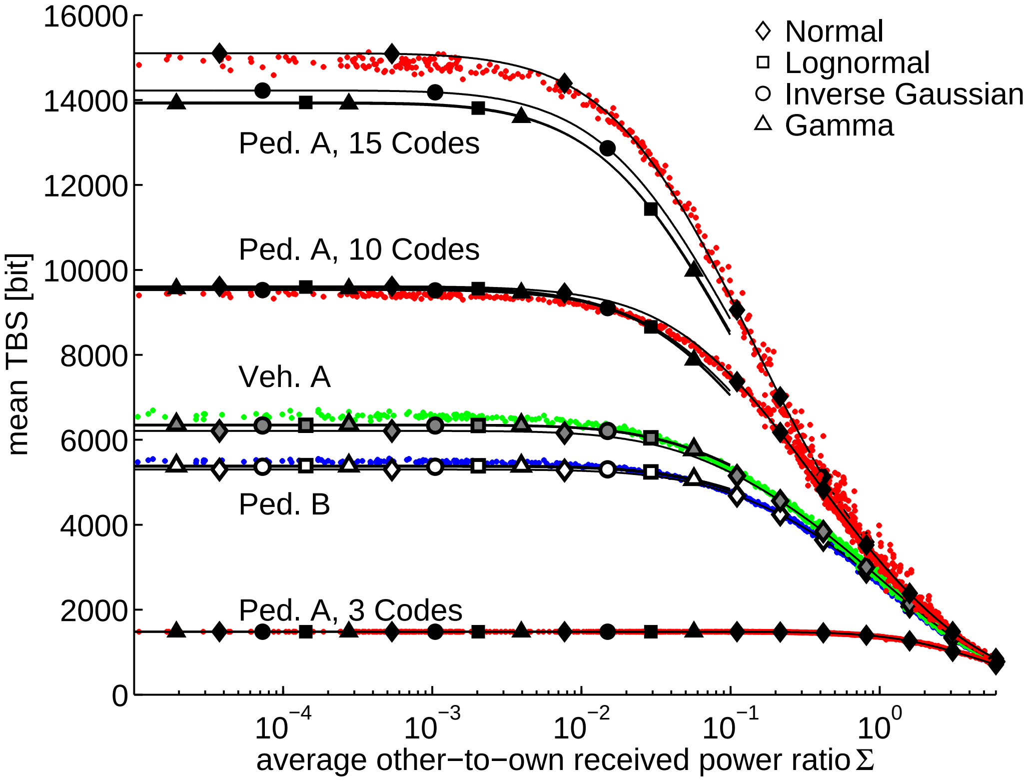
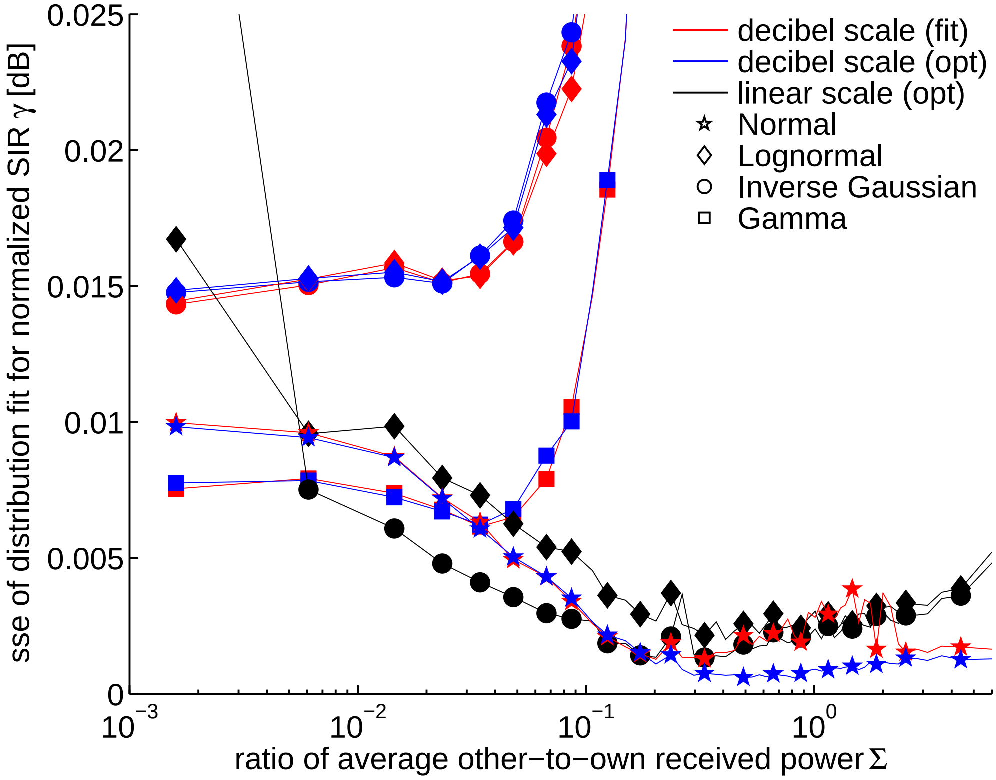
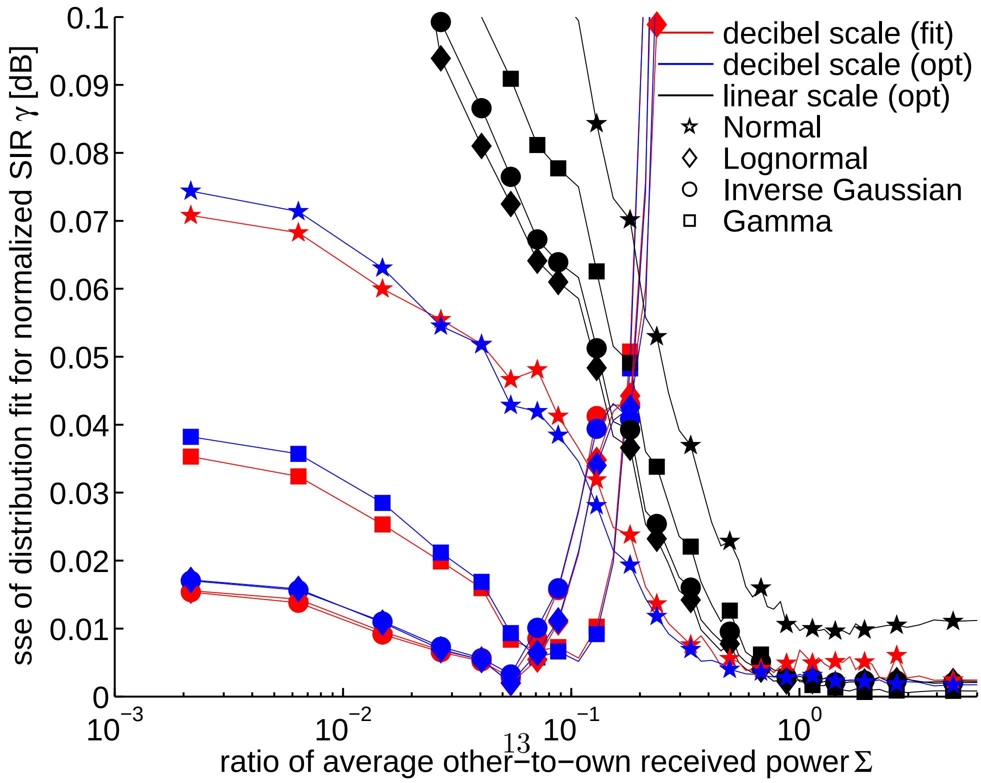


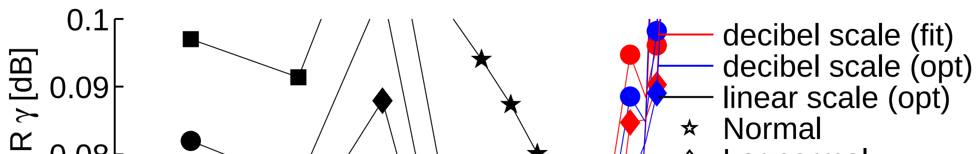
Figure 3: Validation of the mean TBS



(a) ITU Pedestrian A



(b) ITU Pedestrian B



component of the model and also the main contribution of this paper is the estimation of the CQI distribution from the ratio of average other-cell interference to average own-cell interference which can be easily determined for static network situations. The method can be seen as an extension of the orthogonality factor model to cover the whole SIR distribution and not only the mean SIR. One drawback of the model is that the parameters found for the Weibull functions are quite specific for the multi-path profiles and not as easily scalable as the orthogonality factor. In this paper we focused on deriving the mean data volume transmitted in certain period of time when round-robin scheduling is applied. The model also allows to consider other scheduling disciplines like maxCQI-scheduling or proportional fair scheduling.

The method is applicable in Monte Carlo simulations, in high-level time dynamic simulations and analytic models. As an example please refer to [13] for an analytic model based on this method or to [14] where the method is used to investigate HSDPA resource allocation strategies by system-level simulations.

A further advantage of this method is that it is entirely described by the set of parameters for the Weibull functions. That makes it easily applicable for researchers that do not have a physical layer simulator at their disposal. Furthermore, the usage of this model can make simulations from different researchers better comparable since the impact of the lower layer is clearly defined.

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