Spatial Traffic Heterogeneity in HSDPA Networks and its Impact on Network Planning

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Abstract. We quantify the effect of the spatial throughput unfairness that is inherently induced by HSDPA’s link adaptation and channel-aware scheduling techniques, on the spatial distribution of on-going data transfers, and assess its sensitivity with respect to the selected packet scheduler and the offered traffic load, utilising both stochastic analysis and dynamic simulations. Moreover, we investigate the QoS impact of inadequately incorporating the induced spatial traffic heterogeneity in the 3G planning process.

1 INTRODUCTION

In support of the anticipated dominant share of low mobility, delay-tolerant services, and the foreseen up-/downstream traffic asymmetry, 3GPP’s Release 5 specifications of the UMTS standard incorporate a significant technogical upgrade in the form of high Speed Downlink Packet Access [1, 8] (HSDPA). The HSDPA objectives are to boost transfer rates, with peak rates in the range of 8 − 10 Mbits/s, enhance resource efficiency and improve service quality for downlink data transfer. To this end, HSDPA introduces the High Speed Downlink Shared Channel (HS-DSCH) as an upgraded version of the Downlink Shared Channel that is available in ‘basic’ UMTS. The HS-DSCH, which is parameterised by an assigned transmission power rather than an assigned transfer rate, is characterised by a number of enhanced technologies, viz. higher order modulation, fast Adaptive Modulation and Coding (AMC), fast scheduling and hybrid ARQ, operated by the NODE-B.

As a consequence of the AMC and scheduling operations, UEs (User Equipment) close to the base station are favored over more distant UEs and hence the spatial traffic distribution tends to be skewed towards the cell boundaries. The objective of this paper is (i) to assess this spatial traffic heterogeneity for different schedulers and a range of data traffic loads, utilising both stochastic analysis and dynamic simulations; and (ii) to assess the QOS impact of inadequately incorporating the induced spatial traffic heterogeneity in the Monte Carlo-based planning process.

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The majority of publications on HSDPA performance concentrates on link or system level simulations of HSDPA’s AMC and scheduling performance, not specifically assessing the impact of HSDPA on the spatial traffic heterogeneity and the induced effect on network planning [7, 11]. Applying both analytical techniques and dynamic simulations, in [2] the conditional expected QoS is determined as a function of the UE-to-NODE-B distance, observing the strong spatial unfairness that motivates our work. The same observation is made in [3]. Addressing the impact of HSDPA on UMTS network planning, in [13] the Monte Carlo-based evaluation techniques generally applied in 3G network planning are stressed to inherently neglect dynamic system aspects such as multipath fading, which is particularly questionable in HSDPA networks in light of the AMC and scheduling operations. Therefore, [13] proposes an integrated approach of Monte Carlo and dynamic simulations.

The outline of the paper is as follows. Section 2 explains the impact of the AMC and scheduling operations on the spatial traffic distribution. Section 3 gives an overview of UMTS/HSDPA network planning, emphasising the inherent drawbacks of applying Monte Carlo techniques. Section 4 specifies the model assumed in the performance assessment. The performance evaluation approach is detailed in Section 5, while the numerical results are presented in Section 6. Section 7 ends this paper with some concluding remarks.

2 THE EFFECT OF THE HSDPA PRINCIPLES ON THE SPATIAL TRAFFIC DISTRIBUTION

Among the HSDPA principles, the AMC and channel-aware scheduling schemes are anticipated to have a significant endogeneous effect on the spatial distribution of traffic. Since these mechanisms are key in the pursued objectives, they are described in more detail.

AMC replaces transmit power control as the link adaptation mechanism and is applied at the Transmission Time Interval (TTI) time scale based on the CQI (channel quality indicator) feedback from the UE. The objective is to optimise transfer rates for actual channel conditions, e.g. higher-order modulation with little forward error correction redundancy for a UE experiencing favourable fading conditions. Aside from adapting the modulation and channel coding parameters, another link attribute assigned by the AMC scheme is the number of channelisation codes (of fixed spreading factor 16) applied in parallel. Since remote data flows generally experience worse radio link qualities than nearer data flows, the AMC scheme establishes that remote data flows are served at lower transfer rates. As a consequence, the transfer time of a given file or WWW page is longer and thus, when observing the system at a randomly chosen time instant (as is done in Monte Carlo simulations) an above-proportional number of active data flows is typically located at more remote locations. In other words, the AMC operations skew the spatial traffic distribution to have more weight near the cell boundary: ‘AMC EFFECT’.

A fast scheduler coordinates the (potentially) channel-aware sharing of the HS-DSCH among multiple data flows at the TTI time scale, based on the CQI feedback information. An extreme incidence of exploiting channel variations which greedily maximises instantaneous system throughput is pure SNR-based scheduling, i.e. always serve the UE with the most favourable instantaneous channel conditions. Another (channel-oblivious) scheduler is the Round Robin (RR) scheduler. The choice of scheduling scheme influences the apparent trade-off between resource efficiency and fairness. Since remote data flows
are generally served at lower rates than nearer data flows due to AMC, they are served less frequently by a typically implemented channel-aware packet scheduler. This further increases their transfer times and thus magnifies the skewness of the spatial traffic distribution: ‘SCHEDULING EFFECT’.

3 ON 3G NETWORK PLANNING

UMTS/HSDPA network planning tools usually apply Monte Carlo-based simulations [9, 14] as a compromise between a sufficiently realistic incorporation of the complex WCDMA technology and the traffic- and propagation-related dynamics of a live network, and the speed of performance evaluation. In this approach, a large number of independent snapshots are generated for a given scenario, that represent sampled realisations of e.g. the number of active sessions of different types, the locations of the associated UEs and the path gains experienced on the radio links between all NODE-Bs and UEs. For the given snapshot, an iterative link adaptation procedure is applied in order to determine a.o. the assigned transmission powers, transfer rates and interference levels. The evaluation of a snapshot is subsequently wrapped up by administering the relevant performance measures, e.g. outage/blocking probabilities and data throughputs. Once sufficient snapshots are considered in order to attain the desired statistical accuracy, the scenario evaluation is complete. Hence the defining characteristic of Monte Carlo-based evaluations is that it assesses system and service level performance from multiple snapshots, i.e. frozen system states at some time instants, of (a simplified model of) an inherently dynamic system. This induces two generic types of associated shortcomings.

Firstly, a snapshot-based modelling approach inherently ignores the evolution of system aspects that are dynamic in nature, which are therefore omitted or explicitly incorporated in a more or less approximate manner. One example of this is the on-off process that characterises a speech call (silence/speech periods) or WWW session (due to e.g. TCP flow control), which is typically approximated in Monte Carlo-based simulations by means of an activity factor. An HSDPA-related example is that a 3G Monte Carlo-based planning tool generally assumes that traffic is generated according to some exogeneously given spatial distribution, while the HSDPA operations endogenously affect the spatial distribution of data flows (see Section 2). In addition, it assumes a priori knowledge on the (distribution of the) number of present data flows, whereas this is also endogenously determined, as it is directly affected by the data flows’ transfer time distribution. In contrast, for e.g. the speech telephony service, the call holding time distribution and hence also the distribution of the number of present speech calls can be exogenously determined.

Secondly, the extraction of relevant performance measures is more challenging in Monte Carlo-based evaluations. As a consequence of not incorporating the system dynamics, the derived performance measures are intrinsically time-centric in nature, whereas in practice most relevant performance measures have a flow-centric character. As an illustrative example, the blocking probability is a flow-centric measure and is therefore in principle hard to assess from Monte Carlo-based simulations. Fortunately, in case of Poisson arrival processes, the PASTA (Poisson Arrivals see Time Averages) property [12] can be applied in order to effectively claim that the flow blocking probability is equal to the fraction of time that the system is locally congested. The PASTA property thus connects a desired flow-
an obtainable time-centric measure. As another example, the flow transfer time is a relevant flow-centric performance measure for data services. This measure is influenced by the system evolution during a flow transfer and can thus intrinsically only be determined in a dynamic setting, i.e. by means of dynamic simulations or stochastic analysis of a dynamic system, where the flow is considered for its entire duration rather than only at a single time instant. A number of relevant performance measures can therefore not be adequately derived from Monte Carlo-based simulations, e.g. the obtainable time-average throughput may significantly differ from the more relevant flow-average throughput measure. Other examples of relevant yet unobtainable performance measures include the distribution or higher moments of measures, e.g. flow transfer time variance, flow throughput percentiles or packet delay variation. Note, however, that the flow-centric expected transfer time $E\{T\}$ can be obtained from the time-centric expected number of present flows $E\{N\}$ by Little’s law: $E\{N\} = \lambda E\{T\}$, where $\lambda$ denotes the effective flow arrival rate [12].

4 MODEL

In this section the system model, scheduling schemes, propagation aspects and traffic characteristics are specified from the perspective of dynamic simulations, while some remarks are added on the implementation in Monte Carlo simulations.

We consider a 19-cellular UMTS/HSDPA network of omnidirectional NODE-Bs in a hexagonal layout with an inter-NODE-B distance of 1 km. A wraparound technique is applied in order to mimic an infinite network and avoid undesirable network boundary effects. At each NODE-B a Common Pilot Channel is transmitted at a power of 1 Watt, while another constant downlink transmission power of 6 Watt models the presence of other downlink traffic, e.g. speech calls. Each NODE-B is assumed to provide a single HS-DSCCH for data transfer, characterised by a fixed transmission power of 3 Watt. The SNR measured by the UEs is mapped to a reported CQI according to (see [5])

$$CQI = \min\left\{0, \max\left\{0, \frac{SNR}{1.02} + 16.62\right\}\right\}, 22\right\}.$$

As outlined in Section 2, the AMC mechanism in the serving NODE-B maps the reported CQI to the most appropriate link attributes, which determine the applied Transport Block Size (see [1]; UE categories 1-6) and effectively vary the gross data rates from 0 (CQI = 0) to 3.6 Mbits/s (CQI = 22). A transferred data block experiences a BLER which is a function of the applied link attributes (directly determined by the CQI) and the experienced SNR. We apply the following relation between BLER, CQI and SNR, as derived in [5] by means of detailed link-level simulations:

$$BLER = \left\{10^{\left(\frac{\Delta SNR - 1.03CQI + 17.3}{\sqrt{3} - \log_{10}(CQI)}\right)} + 1\right\}^{-\frac{1}{0.7}}.$$

A spatially uniform thermal noise level of $-99$ dBm is considered.

Two distinct scheduling schemes are considered: the channel-oblivious Round Robin (RR) scheme and the channel-aware SNR-based scheduler (see e.g. [7,11,15]). The RR scheduler cyclically serves the present data flows with positive CQI at the TTI heartbeat,
and is thus intrinsically fair in the sense that each data flow gets an egalitarian share of the HS-DSDCH resources. The SNR-based scheduler bluntly exploits the channel quality variations due to multipath fading, in the sense that in each TTI it serves the data flow with the most favourable instantaneous channel conditions, reflected by the reported CQI. RR tie-breaking is applied in case multiple data flows have identical CQIs. The SNR-based scheduler thus greedily maximises the instantaneous system throughput at the anticipated cost of a reduced fairness among data flows, as near UEs are more likely to be served than remote UEs. In Monte Carlo simulations, the RR packet scheduler is implemented such that the NODE-B randomly selects an associated data flow with positive CQI for data transfer, whereas the SNR-based scheduler picks the data flow with the highest CQI, applying random selection as a tie-breaking rule.

The radio propagation model considers distance-based signal attenuation with a path loss exponent of 3.523, and a multipath propagation model with Rayleigh fading on three dominant rays (Pedestrian A model; Jakes’ Rayleigh fading model) and a fading velocity of 0.8 m/s. In Monte Carlo simulations, instantaneous realisations of the Rayleigh fading process are sampled from an exponential distribution with unit mean.

The considered UMTS/HSDPA network serves data flows which are assumed to be downlink transfers of documents. The data flow size is sampled from a hyperexponential distribution with mean $1/\mu = 320$ kbits and a coefficient of variation of 3. The data flows are generated according to a spatially homogeneous Poisson process with a network-wide arrival rate $\lambda \in \{\approx 0, 9.5, 19, \cdots, 57\}$ flows/s. Often ignored in other studies, our model thus incorporates the flow level dynamics, i.e. the dynamic fluctuation of the number of concurrent flows competing for shared resources, due to the random initiation and completion of flows at various locations. In Monte Carlo simulations, the traffic characteristics are reflected in the distribution of the number of flows per cell and their spatial distribution.

A network planner’s most natural assumption is to apply a Poisson distribution for the number of flows and a homogeneous spatial traffic distribution, unless specific knowledge is available to indicate otherwise. Important challenges are to specify the mean number of present data flows and to select a more appropriate heterogeneous traffic distribution.

5 PERFORMANCE EVALUATION APPROACH

This section outlines the approach taken in order to achieve the two main objectives of our study as formulated in Section 1. We first present the methods applied to evaluate the spatial traffic heterogeneity, and subsequently describe our approach to assess its impact on network planning. Numerical results will be given and discussed in Section 6.

5.1 Spatial traffic heterogeneity

In order to assess the effect of HSDPA’s AMC and scheduling operations on the spatial traffic distribution, both dynamic simulations and stochastic analysis are applied. Whereas the former method is rather straightforward, the specifics of the latter approach are presented below for both RR and SNR-based scheduling. We limit ourselves to an explicit consideration of the single cell case, referring to the previous work published in [2] for an
outline of how the network case is handled. The pursued spatial traffic distribution is defined by the probability distribution function of the distance from an arbitrarily selected UE to its serving NODE-B at an arbitrary time instant that the system is non-empty.

**Round robin scheduling** Consider a single cell scenario with RR scheduling. Divide the circular area of the considered cell into \( k \) disjunct zones with equal area. For each zone, determine via dedicated Monte Carlo simulations the expected net transfer rate \( r_j, \ j = 1, \cdots, k \), that a data flow in this zone experiences when served, sampling over all possible locations within the considered zone and all possible Rayleigh fading effects. For a given sample, the net data rate is determined via calculation of the experienced SNR, mapping this to the gross data rate and flipping a biased coin to effectuate the impact of the associated BLER.

The considered system with \( k \) zones, RR scheduling and zone-specific net transfer rates \( r_j \), can be modelled by an \( M/G/1 \) processor sharing model with \( k \) flow classes (zones), as also recognised in [2—4]. The model belongs to the class of product-form ‘networks’ and is analytically tractable (see e.g. Cohen [6]). In particular, the joint distribution of the number \( N_j \) of flows of class \( j \) in the system, \( j = 1, \cdots, k \), is given by

\[
\Pr \{ N_1 = n_1, \cdots, N_k = n_k \} = (1 - \rho) \frac{(n_1 + \cdots + n_k)!}{n_1! \cdots n_k!} \prod_{j=1}^{k} \rho_j^{n_j},
\]

with \( \rho_j \equiv \lambda_j / (r_j \mu) \) the traffic load offered to the system in zone \( j \), \( \lambda_j = \lambda / (19k) \) the flow arrival rate in zone \( j \), \( j = 1, \cdots, k \) (recall that the considered network consists of 19 cells), and where \( \rho \equiv \sum_{j=1}^{k} \rho_j \) denotes the aggregate traffic load. The above expression is known to be insensitive to the specific form of the flow size distribution, depending on the mean flow size only. Using (1), the expected number of flows per class is readily derived to be equal to \( E \{ N_j \} = \rho_j / (1 - \rho) \), for \( j = 1, \cdots, k \), while the aggregate number of data flows is equal to \( E \{ N \} = \sum_{j=1}^{k} E \{ N_j \} = \rho / (1 - \rho) \).

The desired spatial traffic distribution is expressed by the equilibrium probabilities \( p_j \equiv \Pr \{ \text{an arbitrarily selected data flow is located in zone } j \ | \ \text{at least one data flow is present in the system} \} \), \( j = 1, \cdots, k \).

**Theorem** In a single cell scenario with RR scheduling, the spatial traffic distribution is given by

\[
p_j = \frac{p_j}{\rho} = \frac{E \{ N_j \}}{E \{ N \}} = \frac{1/r_j}{\sum_{i=1}^{k} 1/r_i}, \ j = 1, \cdots, k.
\]

**Proof**

\[
p_j = \left( \frac{\sum_{n_1, \cdots, n_k} \frac{n_j}{n_1 + \cdots + n_k} \Pr \{ N_1 = n_1, \cdots, N_k = n_k \}}{\Pr \{ N_1 + \cdots + N_k > 0 \}} \right) / \Pr \{ N_1 + \cdots + N_k > 0 \}
\]

\[
= \frac{1 - \rho}{\rho} \sum_{n=1}^{\infty} \frac{1}{n^n} \left\{ \sum_{n_1=0}^{\infty} \cdots \sum_{n_k=0}^{\infty} \frac{(n_1 + \cdots + n_k)!}{n_1! \cdots n_k!} \prod_{i=1}^{k} \rho_i^{n_i} 1_{n_1 + \cdots + n_k = n} \right\}
\]

\[
= \frac{1 - \rho}{\rho} \sum_{n=1}^{\infty} \frac{1}{n^n} \left\{ \sum_{n_j=0}^{\infty} \rho_j \left( \frac{n_j \cdot (n - n_j + 1) \cdots (n - 1)}{n_j!} \right) \left( \rho_1 + \cdots + \rho_{j-1} + \rho_{j+1} + \cdots + \rho_k \right)^{n-n_j} \right\}
\]
\[
\frac{1 - \rho}{\rho} \sum_{n=1}^{\infty} \sum_{j=0}^{n} \binom{n-1}{n_j-1} \rho_j^{n_j} (\rho - \rho_j)^{n-n_j} = \frac{1 - \rho}{\rho} \sum_{n=1}^{\infty} \frac{\rho^n}{n} \frac{\rho_j}{\rho} = \frac{\rho_j}{\rho} = \frac{E\{N_j\}}{E\{N\}}, \text{ for } j = 1, \ldots, k. 
\]

Observe from expression (2) that the spatial traffic distribution is independent of the flow arrival rate \( \lambda \) and the average data flow size \( 1/\mu \), depending only on the zone-specific net transfer rates \( r_j, j = 1, \ldots, k \). In Section 6.1 it will be demonstrated that this no longer holds exactly for the network case.

**SNR-based scheduling** Consider a single cell scenario with SNR-based scheduling. To allow analytical tractability, the effects of multipath fading are ignored and an exponential flow size distribution is assumed. Hence the obtained insights are of a more approximative character. As above, we divide the cell into \( k \) zones where the zone boundaries are now derived such that there is a one-to-one correspondence between the zones and the applied gross transfer rate. The zone-specific expected net transfer rates \( r_j, j = 1, \ldots, k \), are again obtained by Monte Carlo simulation, sampling over all possible locations within the considered zone and thus incorporating the associated effect of the location-dependent experienced SNR on the BLER.

The considered system with \( k \) zones, SNR-based scheduling and net transfer rates \( r_j, j = 1, \ldots, k \), can be modelled by a multi-class \( M/M/1 \) queueing model with a priority-based service discipline. This model is analytically tractable and some relevant performance measures can be derived [2]. The main result is repeated here. Let the flow arrival rate of service class \( j \) be denoted \( \lambda_j, i = 1, \ldots, k \), denote with \( \rho_j \equiv \lambda_j / (r_j \mu) \) the offered traffic load in zone \( j, j = 1, \ldots, k \), and let \( \rho \equiv \sum_{j=1}^{k} \rho_j \) denote the aggregate traffic load. The expected number of data flows in each zone is given by

\[
E\{N_j\} = r_j \left( \frac{\sum_{k=1}^{j} \rho_k}{1 - \sum_{k=1}^{j} \rho_k} - \frac{\sum_{k=1}^{j-1} \rho_k}{1 - \sum_{k=1}^{j-1} \rho_k} \right), \quad j = 1, \ldots, k, \text{ with the convention that the sum } \sum_{k=1}^{0} = 0. 
\]

Unfortunately, we don’t have any results for the joint steady state distribution and hence we can not follow the same approach as for the RR case to derive the spatial traffic distribution \( p_j, j = 1, \ldots, k \) (cf. Theorem 5.1). However, motivated by the simple and easy to generalize result \( \bar{p}_j = E\{N_j\} / E\{N\} \) for RR, we take \( E\{N_j\} / E\{N\} \) as an approximation for the spatial distribution in the case of SNR-based scheduling:

\[
\bar{p}_j \equiv \frac{E\{N_j\}}{E\{N\}}, \quad j = 1, \ldots, k. 
\]

Numerical results obtained from extensive simulations for a broad range of parameter values support this approximation and even suggest that it is exact. A formal analytical proof of this attractive result, however, could not be found.
5.2 Impact on network planning

The second objective of this study primarily addresses the impact of the HSDPA-induced spatial traffic heterogeneity on Monte Carlo-based network planning, while also the aforementioned distinction between the desired flow-centric and the obtainable time-centric throughput measures is investigated. The approach is based on the comparison of five throughput measures that are determined in distinct manners, utilising stochastic analysis, dynamic and Monte Carlo-based simulations (cf. Figure 1).

Flow-average throughput measure $R_1$ is a flow-centric measure that is determined via dynamic simulations by averaging the experienced throughputs for all processed data flows and is the most relevant measure from the customer perspective [10]. Obtained via the same dynamic simulation experiments, time-average throughput measure $R_2$ is determined by averaging the instantaneously experienced per-flow throughputs over time [10] and is included because it provides the most accurate time-average throughput measure and thus serves as the fairest reference measure for Monte Carlo-based measures $R_3$ and $R_4$ defined next. Time-average throughput measure $R_3$ is obtained from Monte Carlo simulations and assumes that the network planner is somehow able to provide the simulation with accurate information regarding both the average number of present flows and their heterogeneous spatial distribution. Reflecting an optimistic best case assumption, this information is extracted from the dynamic simulations. Hence this measure is arguably the most adequate data QoS predictor that can be obtained from a Monte Carlo-based planning tool. Time-average throughput measure $R_4$ is obtained in a similar way as measure $R_3$, but assumes spatial traffic homogeneity and thus supposes a network planner’s unawareness of the HSDPA-induced traffic heterogeneity. This measure is considered because it is based on a natural default assumption of spatial traffic homogeneity, given the considered spatially uniform flow arrival process. Finally, time-average throughput measure $R_5$ is also obtained from Monte Carlo simulations and completely relies on the stochastic analysis presented in Section 5.1 to provide the input information regarding both the average aggregate number of data flows and their heterogeneous spatial distribution.

![Figure 1](image.png)

Fig. 1. Overview of the different throughput measures and how they are obtained from stochastic analysis, dynamic and Monte Carlo-based simulations.
6 NUMERICAL RESULTS

In this section we first investigate how HSDPA’s AMC and packet scheduling operations affect the spatial traffic distribution for different traffic loads, followed by an assessment of the impact of the observed spatial traffic heterogeneity on network planning.

6.1 Spatial traffic heterogeneity

In this subsection the spatial traffic heterogeneity is assessed. First, we present and discuss the simulation results, followed by the results obtained from stochastic analysis.

Simulation results Obtained by means of dynamic simulations, the top pair of charts in Figure 2 show the (normalised) flow-average data throughput (in kbits/s) as a function of a UE’s distance to its serving NODE-B. Both schedulers are considered for \( \lambda \in \{ \approx 0, 9.5, 19, \ldots, 57 \} \), where \( \lambda \approx 0 \) represents a limit case of \( \lambda \to 0 \) where any present data flow is served in an otherwise empty system. Consider the left chart. Observe that for the extreme case of \( \lambda \approx 0 \) the throughput curve is trivially independent of the choice of scheduler as there is never more than a single data flow in service. As a consequence, the impact of the UE-to-NODE-B distance on the experienced throughput is solely due to the AMC effect. As \( \lambda \) increases, both an overall throughput degradation that is due to an increased competition for resources and the distinctive impact of the applied scheduling scheme become apparent. Under SNR-based scheduling, the increased traffic load primarily affects the data flows associated with more distant UEs, which see their experienced throughputs roughly halved for the highest considered \( \lambda \)'s. This is due to the inherent preference of the SNR-based scheduler to serve the data flows with more favourable SNRs, which are typically located nearer to the NODE-B. In contrast, the RR scheduler fairly shares the HS-Dsch resources over all present data flows whether distant or near, and hence the increased \( \lambda \) yields an equivalent relative throughput degradation for all locations. The chart further shows that SNR-based scheduling generally outperforms RR scheduling, even for UEs at the cell edge, as it more efficiently exploits the HS-Dsch resources.

As a perhaps clearer demonstration of the relative performance experienced at different locations, the right chart depicts the throughput performance relative to the reference curve that is associated with the extreme case of \( \lambda \to 0 \). This chart further reveals that for heavy traffic loads, more distant data flows do tend to be (slightly) disadvantaged even under RR scheduling, despite the channel-oblivious scheduler’s inherent fairness property. This can be understood by considering the following additional effect of an increasing traffic load in a multi-cellular scenario. As the traffic load increases, the likelihood that data flows are active at surrounding NODE-Bs increases and hence so does the (inter-cellular) interference level experienced in a given reference cell, primarily by the UEs that are nearest to the cell edge. As a consequence, these UEs experience worse SNRs and, when scheduled, are served at a further reduced data rate.

Obtained from the same dynamic simulations, the bottom pair of charts in Figure 2 depicts the spatial traffic distribution, again for both packet schedulers and the same range of \( \lambda \)'s. The left chart shows the probabilities that an arbitrarily selected data flow at an arbitrary time instant (where the system is non-empty) is located at a certain distance
Fig. 2. The (normalised) flow-average data throughput versus the UE-to-NODE-B distance and the (normalised) spatial traffic distribution, obtained via dynamic simulations.

from the NODE-B. As a reference, the homogeneous distribution is also depicted. This reference curve illustrates the fact that a homogeneous traffic distribution corresponds to a probability mass that is increasing in the UE-to-NODE-B distance, which can be intuitively understood by considering that the ‘area’ of a circle increases with the circle radius\(^3\). The sudden ‘fall-off’ for the largest of distances corresponds with the corners of the hexagons whose associated distances occur only in these corners. In the right chart the spatial traffic distributions have been normalised with respect to the homogeneous distribution, such that a flat line corresponds with a spatially homogeneous distribution.

A number of observations can be made from these charts that correspond closely with the observations made from the throughput charts at the top of the figure. Even though the flow arrivals are spatially homogeneous, the HSDPA operations always induce a significant spatial heterogeneity, regardless of the applied scheduler or the offered traffic load. This is due to the AMC effect: data flows farther from the NODE-B are served at lower

\(^3\) This fact can be more formally derived by converting the homogeneous distribution in the Cartesian \((x, y)\) coordinates into polar \((r, \vartheta)\) coordinates, which gives a marginal probability distribution of the distance \(r\) equal to \(2r/R\).
Analytical results The same trends as observed above from the simulation results are also seen in the numerical results presented in Figure 3, which have been analytically obtained (see Section 5.1; network case) and show only the normalised spatial distribution curves for both schedulers. Recall that the analytical model of SNR-based scheduling ignores the presence of multipath fading, while the flow sizes are exponentially (with coefficient of variation 1) rather than hyperexponentially distributed (with coefficient of variation 3). The absence of multipath fading effectively establishes a larger degree of preference for data flows that are near the NODE-B (see also [2]), and therefore leads to a more extremely skewed spatial traffic distribution, compared to the case with multipath fading considered in the simulation experiments, particularly for heavier traffic loads. Observe that the results regarding the spatial traffic distribution under RR scheduling, closely match the simulation results in both a qualitative and a quantitative sense.

![Fig. 3. The normalised spatial data traffic distribution, obtained via stochastic analysis.](image)

6.2 Impact on network planning
We now assess the impact of the HSDPA-induced spatial traffic heterogeneity on Monte Carlo-based network planning. In addition, we will address the inherent drawback in
Monte Carlo simulations of being restricted to time-centric performance measures, viz. the time- rather than the flow-average throughput.

As mentioned in Section 5, the Monte Carlo simulations are fed with (i) the homogeneous ($\rightarrow$ throughput measure $R_4$) or heterogeneous ($\rightarrow R_3$) traffic distribution depicted in Figure 2 or Figure 3 (not normalised; $\rightarrow R_5$); and (ii) the average number of present data flows that were obtained via dynamic simulations ($\rightarrow R_3$ and $R_4$) or stochastic analysis ($\rightarrow R_5$) and are presented in Table 1. Observe from the table that the average number of present data flows under RR scheduling generally exceeds that for SNR-based scheduling, due to the latter scheduler’s intrinsically more resource efficient character.

<table>
<thead>
<tr>
<th>$\lambda$</th>
<th>FROM DYNAMIC SIMULATIONS</th>
<th>FROM STOCHASTIC ANALYSIS</th>
</tr>
</thead>
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<td>$\approx$ 0.0 flows/s</td>
<td>0.000 flows</td>
<td>0.000 flows</td>
</tr>
<tr>
<td>9.5 flows/s</td>
<td>0.165 flows</td>
<td>0.156 flows</td>
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<td>19.0 flows/s</td>
<td>0.405 flows</td>
<td>0.350 flows</td>
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<td>0.781 flows</td>
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<td>0.906 flows</td>
</tr>
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<td>2.955 flows</td>
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<td>57.0 flows/s</td>
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<td>1.826 flows</td>
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</tbody>
</table>

For both schedulers and the range of considered $\lambda$’s, Figure 4 shows the obtained results for the five throughput measures that have been introduced in Section 5.2. Observe first that for all but the infinitesimally small traffic loads, the SNR-based scheduler outperforms the RR scheduler for all considered performance measures. Furthermore, note that although the different throughput measures all aim to reflect the same QoS experience, significant discrepancies are possible for very plausible scenarios, as also observed in [10]. A few specific comparisons seem appropriate. Firstly, the time-average throughput measure as predicted by the Monte Carlo-based simulator (cf. planning tool) with an adequate consideration of the spatial traffic heterogeneity appears to approximate the same measure obtained via dynamic simulations rather well, as intended. If an assumption of spatial traffic homogeneity is applied, the predicted throughput level is significantly higher, due to the more favourably sampled UE locations. The discrepancy with the time-average throughput in the dynamic system can be well over 50%!

As it turns out, however, this Monte Carlo-based (time-average) throughput measure that is obtained under false assumptions regarding the spatial traffic distribution, closely approximates the most appropriate of all measures, i.e. the flow-average throughput in a dynamic system. This seems to be a rather fortunate case where two mistakes roughly cancel out, viz. deriving a time- rather than flow-centric measure and assuming spatial homo- rather than heterogeneity. As observed in a more generic setting in [10], the time-average data throughput is indeed typically smaller than the flow-average throughput, while on the other hand the false traffic homogeneity assumption is readily understood to have a positive effect on the predicted throughput. Hence both mistakes do indeed cause discrepancies in opposite directions. Still, the observation that their magnitudes are of similar order is to be investigated further, before it can be decided that advanced modifications of Monte Carlo-based evaluations are indeed unnecessary.
Fig. 4. The different average throughput measures, obtained via dynamic/Monte Carlo simulations and stochastic analysis.

Finally, observe for the RR scheduler that the Monte Carlo-based time-average throughput measure that relies entirely on analytically derived (spatially heterogeneous) traffic information is almost identical to the corresponding measure that takes its (spatially heterogeneous) traffic information from dynamic simulations. This is in agreement with the similar spatial traffic distributions that were shown in Figures 2 and 3. As this similarity did not hold for the SNR-based scheduler, due to the absence of fast fading in the stochastic analysis, the corresponding throughput measures also differ significantly.

7 CONCLUDING REMARKS

In this paper, we have studied the spatial traffic heterogeneity resulting from HSDPA’s AMC and (channel-aware) scheduling operations in a 3G radio network and its implications on the planning process, where it is usually assumed that the spatial distribution of ongoing flows corresponds with the spatial distribution of newly generated flows. Quantitative results have been obtained and compared for two different HSDPA fast scheduling algorithms, i.e. RR and SNR-based scheduling.

From extensive dynamic simulations and from analytical models we can conclude that the spatial heterogeneity is largely caused by the inherent effect of the flows’ distances to the NODE-B on the achievable throughput. The applied scheduling algorithm appears to have a less significant effect. Spatial heterogeneity is indeed more pronounced for SNR-based scheduling than for RR, but the difference appears to be much smaller than intuitively expected. This is due to the fact that the preference of the SNR-based scheduler for flows close to the base station eventually also has a positive effect on the performance of data flows at the cell boundary, viz. flows close to the NODE-B are served more quickly, and hence compete only shortly with the other data flows.

In order to investigate the implications of the spatial traffic heterogeneity for radio network planning, we have compared the realistic throughput values mentioned above (i.e. obtained via dynamic simulations) with the throughput values resulting from Monte Carlo-based simulations generally applied in the network planning process. We have ar-
gued that the Monte Carlo simulation introduces two main sources of errors: (i) an error due to the inherent fact that the Monte Carlo simulator measures time-average throughputs instead of the more relevant flow-average throughputs resulting from the dynamic simulations; and (ii) an error due to wrong assumptions about the spatial traffic distribution of ongoing flows. The numerical results show that both errors cause discrepancies in opposite directions and even appear to roughly cancel out. Although the observed phenomenon seems attractive, the significance of each individual discrepancy is sufficiently large to motivate a more extensive numerical assessment in order to verify thoroughly whether the network planner can indeed safely combine these inappropriate assumptions.

REFERENCES