The Asymptotic Limits of Interference in Multicell Networks with Channel Aware Scheduling

Paul de Kerret and David Gesbert
Mobile Communication Department, Eurecom
2229 route des Crêtes, 06560 Sophia Antipolis, France
{dekerret,gesbert}@eurecom.fr

***Abstract*—Interference is emerging as a fundamental bottleneck in many important wireless communication scenarios, including dense cellular networks and cognitive networks with spectrum sharing by multiple service providers. Although multiple-antenna signal processing is known to offer useful degrees of freedom to cancel interference, extreme-value theoretic analysis recently showed that, even in the absence of multiple-antenna processing, the scaling law of the capacity in the number of users for a multi-cell network with and without inter-cell interference was asymptotically identical provided a simple signal to noise and interference ratio (SINR) maximizing scheduler is exploited. This suggests that scheduling can help reduce inter-cell interference substantially, thus possibly limiting the need for multiple-antenna processing. However, the convergence limits of interference after scheduling in a multi-cell setting are not yet identified. In this paper[1] we analyze such limits theoretically. We consider channel statistics under Rayleigh fading with equal path loss for all users or with unequal path loss. We uncover two surprisingly different behaviors for such systems. For the equal path loss case, we show that scheduling alone can cause the residual interference to converge to zero for large number of users. With unequal path loss however, the interference power is shown to converge in average to a nonzero constant. Simulations back our findings.**

I. Introduction

Interference management is a tool instrumental in reaching the high spectrum efficiencies required by future wireless networks. Cooperation and sharing of the users data between the base stations (BS) leads to the so-called multi-cell multiple-input multiple-output (MIMO) network [1], [2] which allows for spatial nulling of the interference. However, the requirement on the backhaul structure and the feedback are extremely high and have brought the need for more practical distributed approaches. Alternatively, multiuser diversity is well known to provide capacity gains via the scheduling of UEs with good channel gains [3] and also appears as a promising tool to manage interference. For instance, in the single cell scenario, it was shown that thanks to multiuser diversity it was possible to achieve close to the performances of dirty paper coding with a simple random beamforming scheme, when the number of user equipment (UEs) becomes large [4], [5]. This principle was extended to the multicell setting when communication is allowed between the BSs [6]. In [7], the improvement brought by intercell scheduling was studied, and scheduling combined with a zero forcing (ZF) precoding scheme was discussed for the Wyner channel in [8]. The sum rate scaling was studied for particular types of information traffic when the number of antennas grows large in [9], and asymptotically in terms of the number of transmitter-receiver pairs in [10]. These works are among the many recent examples suggesting the beneficial impact of scheduling in interference-limited MIMO networks. Beyond the assumption of some kind of multiple antenna processing, previous schemes also assume some fast exchange of channel state information between the cells, making it difficult to scale in certain practical scenarios with limited backhaul communications.

In [11], the impact of the scheduler over the scaling law of capacity in many-user networks was analyzed along with the existence of distributed solutions which reduce largely the complexity for small costs. There, a *simple distributed max-SINR scheduler* has been shown to lead to the same scaling in terms of the number of UEs per cell as the *no-interference upper bound* corresponding to the rate of a setting with no interfering cell. This extreme-value theoretic result suggests that scheduling alone can significantly reduce the degradation brought by interference, thus confirming a general intuition in our community. Nevertheless it is not clear from existing studies whether scheduling alone can fully eliminate interference or merely reduce it (even asymptotically) since this distinction is not visible from scaling law analysis.

Our main contribution is to answer theoretically some of these questions and the main findings are now summarized.

In the symmetric case (i.e. when the UEs are subject to the same path loss), the average difference between the no-interference upper bound and the rate using the max-SINR scheduler is shown to vanish as a $O(log(log(n))/log(n))$, where n is the number of UEs per cell. The interference power after scheduling is also shown to converge to zero.

Interestingly, we prove that, on the opposite, the average interference power converges to a nonzero constant in the asymmetric case (i.e. when the UEs are subject to an individual location dependent path loss). This shows that rate-maximizing scheduling alone is unable to fully eliminate interference in realistic networks.[2]

[1]Discussions with Dr. Marios Kountouris are thankfully acknowledged. This work has been performed in the framework of the European research project ARTIST4G, which is partly funded by the European Union under its FP7 ICT Objective 1.1 - The Network of the Future.

[2]This does not preclude other non rate-optimal schedulers to eliminate interference, for instance an interference-minimizing scheduler.

Notations: The base 2 logarithm is denoted by $\log$. We write $g(n) = O(f(n))$ if $\exists K > 0, \lim_{n\to\infty} g(n)/f(n) = K$. If $\lim_{n\to\infty} g(n)/f(n) = 0$, we write $g(n) = o(f(n))$ and we use $g(n) \sim f(n)$ to denote $g(n) - f(n) = o(f(n))$.

II. System Model

A. Description of the Transmission Scheme

We consider the downlink transmission in a multicell wireless network where in each cell one base station (BS) transmits to one user equipment (UE). The BSs and the UEs have each one antenna, and the UEs receive interference from N neighboring cells. We assume that n UEs are located in each cell and apply single user decoding. Moreover, only one UE at a time is selected for transmission in each cell. The additive noise is zero-mean white Gaussian with a variance of one. For the scheduling decision phase, all the BSs transmit at their maximal power P, and the schedulers are applied at each BS separately, so that we study only one cell w.l.o.g.

In the cell considered, the gain of the direct link to UE k is denoted by $\gamma(k)G(k) \in \mathbb{R}^+$, where $\gamma(k)$ represents the path loss, $G(k)$ is a random variable modeling the short term fading, and the two random variables are independent from each other and independently distributed for each UE. Shadow fading is not considered in this particular paper. Similarly, the gain of the link from the interfering BS j to UE k is denoted by $\gamma_j(k)G_j(k) \in \mathbb{R}^+$. Thus, the SINR at UE k is written as

$$\text{SINR}(k) \triangleq \frac{P\gamma(k)G(k)}{1 + \sum_{j=1}^{N} P\gamma_j(k)G_j(k)}, \forall k \in [1, n]. \quad (1)$$

We also define the short notations

$$\alpha_k \triangleq P\gamma(k)G(k), \quad \beta_k \triangleq \sum_{j=1}^{N} P\gamma_j(k)G_j(k), \quad \forall k \in [1, n].$$

We focus on distributed schedulers, i.e., which use only local CSI. The *max-SINR* scheduler is an example of such scheduler. The SINR at the UE is then maximized and is written as

$$\Gamma(\alpha_n^*, \beta_n^*) \triangleq \max_{k\in[1,n]} \left(\frac{\alpha_k}{1+\beta_k}\right). \quad (2)$$

We will compare this SINR with the *no-interference* upper bound, indexed with 'up', obtained by considering a setting with no interfering cell. The SINR upper bound after scheduling is then $\alpha_n^{\text{up}*} \triangleq \max_{k\in[1,n]} \alpha_k$. The rates follow then as

$$\begin{aligned} R(\alpha_n^*, \beta_n^*) &\triangleq \log(1 + \Gamma(\alpha_n^*, \beta_n^*)) \\ R_{\text{up}}(\alpha_n^{\text{up}*}) &\triangleq \log(1 + \alpha_n^{\text{up}*}). \end{aligned} \quad (3)$$

We will interest ourselves in the remaining interference power after max-SINR scheduling β_n^*, particularly its asymptotic behavior when the number of UEs per cell tends to infinity. It is also linked to the average difference between the rate obtained in the no-interference case and the rate obtained with the max-SINR scheduler, denoted as

$$\Delta_R(n) \triangleq \mathrm{E}\left[R_{\text{up}}(\alpha_n^{\text{up}*})\right] - E\left[R(\alpha_n^*, \beta_n^*)\right] \quad (4)$$

which will be our second main focus. We will study these two parameters for each of the two channel models and use them to quantify the efficiency of the max-SINR scheduler.

B. Channel Models

We now recall the description of the two channel models considered which we call the *symmetric* and the *asymmetric* model, depending on whether the UEs have equal path loss or not, respectively. For both cases, we model a cell as a disc of radius R instead of the hexagonal shape.

1) The Symmetric Model: In the symmetric model, we assume that all the UEs have the same path loss. It is an interesting theoretical case, that we model in our cellular model by letting all the UEs be located at the same distance of the serving BS, i. e., on a circle of radius R_{sym}. The path loss is denoted as $\gamma(k) = \gamma$.

2) The Asymmetric Model: In the asymmetric model, the UEs are distributed uniformly inside the disc of radius R. According to a generic path loss model, we have $\gamma(k) = \lambda d(k)^{-\varepsilon}$ and $\gamma_j(k) = \lambda d_j(k)^{-\varepsilon}$, with λ a scaling factor, ε the path loss exponent (usually between 2 and 4 roughly), and $d(k)$ (resp. $d_j(k)$) the distance between the UE and the mother (resp. j-th interfering) BS. Note that the exact shape of the cell has no impact asymptotically because the max-SINR scheduler tends to select UEs inside the cell and away from the border region.

III. Asymptotic Analysis in Symmetric Networks

The scaling of the average throughput after max-SINR scheduling in terms of the number of UEs per cell was derived in [5] in the case of the broadcast transmission from a single BS with several antennas. In the following, we give three lemmas which will lead us to an extension of the asymptotic results to the multicell case and to an evaluation of the rate offset and the convergence speed. Particularly, in Lemmas 1 and 2 we derive approximations with neglected terms in the order of $o(1)$, i.e., which asymptotically vanish. In lemma 3, the results are extended to the transmission from non-collocated antennas where the path loss from the different interfering signals are a priori unequal. The detailed proofs of the lemmas can be found in [12].

Lemma 1. *In symmetric networks with a large number of UEs per cell, the average rate $E\left[R_{up}(\alpha_n^{up*})\right]$ is upper bounded as*

$$E\left[R_{up}(\alpha_n^{up*})\right] \le f(n) + \frac{\log(\log(n))}{\log(n)} + o\left(\frac{\log(\log(n))}{\log(n)}\right)$$

with $f(n) \triangleq \log(\rho\log(n))$, and lower bounded as

$$E\left[R_{up}(\alpha_n^{up*})\right] \ge f(n) - \frac{\log(\log(n))}{\log(n)} + o\left(\frac{\log(\log(n))}{\log(n)}\right).$$

Lemma 2. *In symmetric networks, with the assumption that the path loss from all the interfering BSs are equal to γ, the average rate $E\left[R(\alpha_n^*, \beta_n^*)\right]$ can be upper bounded as*

$$E\left[R(\alpha_n^*, \beta_n^*)\right] \le f(n) - (N-1)\frac{\log(\log(n))}{\log(n)} + o\left(\frac{\log(\log(n))}{\log(n)}\right)$$

where $f(n) \triangleq \log(\rho\log(n))$, and lower bounded as

$$E\left[R(\alpha_n^*, \beta_n^*)\right] \ge f(n) - (N+1)\frac{\log(\log(n))}{\log(n)} + o\left(\frac{\log(\log(n))}{\log(n)}\right)$$

Lemma 3. *Lemma 2 holds also when the path loss between the interfering BSs and the UE are not equal to each other.*

Combining these three lemmas, it can be directly shown that the difference between the average rates from the no-interference upper bound and the max-SINR scheduler asymptotically vanishes. Moreover, the rate of convergence is also derived, as stated in the following theorem.

Theorem 1. *In symmetric networks, the rate difference $\Delta_R(n)$ defined in* (4) *vanishes as the number of UEs per cell tends to infinity. Moreover, for $N \geq 3$, we have that*

$$\Delta_R(n) = O\left(\frac{\log(\log(n))}{\log(n)}\right). \tag{5}$$

The following result follows easily with the proof in [12].

Corollary 1. *The interference power β_n^* tends almost surely to zero.*

Theorem 1 shows that a distributed max-SINR scheduler is asymptotically sufficient to cancel the interference from interfering cells. However, we show here also that the convergence is extremely slow and it will be confirmed by simulations that for realistic number of UEs per cell the average rate difference remains significant, thus implying that the interference cannot be handled only by the distributed max-SINR scheduler in practical network sizes.

IV. Asymptotic Analysis in Asymmetric Networks

Here we are interested in whether the above analysis extends to the more realistic case of unequal path loss across UEs. In fact, the analysis reveals a surprisingly different behavior. We start by deriving the scaling of the average rates and we then focus on the asymptotic behavior of the post-scheduling interference power.

Proposition 1. *In asymmetric networks, the average rate for the no-interference upper bound is asymptotically equivalent to the average rate achieved with the max-SINR scheduler, and both are asymptotically equivalent as follows.*

$$E\left[R_{up}\left(\alpha_n^{up*}\right)\right] \sim E\left[R\left(\alpha_n^*, \beta_n^*\right)\right] \sim \frac{\varepsilon}{2}\log(n). \tag{6}$$

Proof: A detailed proof is given in [12]. ■

Thus, most of the no-interference upper bound average rate can be asymptotically achieved by a max-SINR scheduler without other interference management scheme. However, this does not state anything on the average rate difference and more accurate analysis is needed.

Theorem 2. *The average interference power after max-SINR scheduling $E[\beta_n^*]$ converges to a strictly positive constant β_∞^* when the number of UEs goes to infinity.*

Proof: We will show the theorem by contradiction. Let assume that β_n^* converge in average to zero. It implies that it converges almost surely to zero, which is written as

$$\forall \eta > 0, \exists n_\eta > 0, n > n_\eta \Rightarrow \beta_n^* < \eta, \text{ almost surely} \tag{7}$$

Since $(\beta_k)_k$ is i.i.d. non negative, we have that $\Pr\{\beta_k \leq \eta\} = P_\eta$, with P_η tending to zero as η tends to zero. We now choose arbitrarily an $\eta > 0$ and $n > n_\eta$, such that

$$\begin{aligned}\mathrm{E}\left[R\left(\alpha_n^*, \beta_n^*\right)\right] &= \mathrm{E}\left[R\left(\alpha_n^*, \beta_n^*\right) \middle| \beta_n^* \leq \eta\right] P\left(\beta_n^* \leq \eta\right) \\ &\quad + \mathrm{E}\left[R\left(\alpha_n^*, \beta_n^*\right) \middle| \beta_n^* > \eta\right] P\left(\beta_n^* > \eta\right) \\ &= \mathrm{E}\left[R\left(\alpha_n^*, \beta_n^*\right) \middle| \beta_n^* \leq \eta\right] P\left(\beta_n^* \leq \eta\right) + \epsilon_1(\eta)\end{aligned} \tag{8}$$

where we have defined $\epsilon_1(\eta) \triangleq \mathrm{E}\left[R\left(\alpha_n^*, \beta_n^*\right) \middle| \beta_n^* > \eta\right] P\left(\beta_n^* > \eta\right)$. We can then upper bound the conditional expectation by neglecting the interference power:

$$\begin{aligned}\mathrm{E}\left[R\left(\alpha_n^*, \beta_n^*\right)\right] &\leq \mathrm{E}\left[\log\left(\max_{k\in[1,n]} \alpha_k\right) \middle| \beta_n^* \leq \eta\right] + \epsilon_1(\eta) + o(1) \\ &= \mathrm{E}\left[\log\left(\alpha_{P_\eta n}^{\mathrm{up}*}\right)\right] + \epsilon_1(\eta) + o(1) \\ &= \frac{\varepsilon}{2}\log(P_\eta n) + \epsilon_1(\eta) + \epsilon_2(P_\eta n)\end{aligned}$$

where we have used to obtain the second equality that β_k and α_k are independently distributed such that considering the UEs verifying $\beta_k < \eta$ is equivalent in terms of average sum rate as considering randomly chosen $P_\eta K$ UEs. We have also defined $\epsilon_2(n) \triangleq \mathrm{E}\left[R_{\mathrm{up}}\left(\alpha_n^{\mathrm{up}*}\right)\right] - \varepsilon/2\log(n) = o(\log(n)$ using Proposition 1. We now define $g(n) \triangleq \varepsilon/4\log(n) + \epsilon_2(n)$ which is increasing in n for n large enough. Thus, we obtain

$$\begin{aligned}\mathrm{E}\left[R\left(\alpha_n^*, \beta_n^*\right)\right] &\leq \tfrac{\varepsilon}{4}\log(P_\eta n) + g(P_\eta n) + \epsilon_1(\eta) \\ &\leq \tfrac{\varepsilon}{4}\log(P_\eta n) + g(n) + \epsilon_1(\eta).\end{aligned} \tag{9}$$

On the other side, we consider the lower bound obtained with a scheduler maximizing only the gain of the direct link, which we call the *max-gain* scheduler.

$$\begin{aligned}\mathrm{E}\left[R\left(\alpha_n^*, \beta_n^*\right)\right] &\geq \mathrm{E}\left[\log\left(1 + \frac{\max_{k\in[1,n]}(\alpha_k)}{1+\beta_k}\right)\right] \\ &= \mathrm{E}\left[\log\left(\alpha_n^{\mathrm{up}*}\right)\right] - \mathrm{E}\left[\log(1+\beta_k)\right] + o(1) \\ &= \frac{\varepsilon}{4}\log(n) + g(n) - C_{\mathrm{LB}} + o(1)\end{aligned}$$

where we have defined the constant $C_{\mathrm{LB}} \triangleq \mathrm{E}\left[\log(1+\beta_k)\right]$. The difference between the upper bound and the lower bound is denoted by Δ_{bounds} and is directly computed to be equal to

$$\Delta_{\mathrm{bounds}} \triangleq \frac{\varepsilon}{4}\log(P_\eta) + C_{\mathrm{LB}} + \epsilon_1(\eta). \tag{10}$$

This equation holds for any η and we can find η so that P_η and $\epsilon_1(\eta)$, who tend both to zero as η tend to zero, are small enough to obain a negative Δ_{bounds}. This is a contradiction, and we conclude that β_n^* does not tend to zero.

Moreover, the SINR is decreasing in β_k and $(\beta_k)_k$ is statistically independent from $(\alpha_k)_k$. Thus, the max-SINR scheduler improves the distribution of β_k towards smaller values. Increasing the number of UEs can only lead to a reduction of $\mathrm{E}[\beta_n^*]$, which is thus lower bounded by a strictly positive number and non increasing, thus converges to a non-zero positive number. ■

Corollary 2. *The average rate difference $\Delta_R(n)$ does not tend to zero as $n \to \infty$.*

Proof: A detailed proof is given in [12]. ■

The scheduler alone is unable to fully eliminate the inter-cell interference when path loss is accounted for. The intuitive explanation is that the scheduler can gain much more by finding UEs with a more favorable path loss rather than trying to find those with a small interference power. The difference with the symmetric model is that the increase of received power from the reduced path loss in the asymmetric model is much larger than the increase of the direct gain from the Rayleigh fading in the symmetric case. Thus, the incentive to reduce the interference power is much smaller in the asymmetric model. Clearly, this leads to a highly unfair scheduler which favors UEs closer to their serving BS.

Simulating the cumulative distributive function of the interference power after scheduling in fact shows that the interference power after max-SINR scheduling converges in distribution to a limiting distribution which is very close to the original distribution of the interference power.

V. Simulations

We simulate a multicell networks with the interference from the first ring of interferer with full frequency reuse. We consider the propagation parameters of the LTE cellular network for the Hata urban scenario path loss model. Our parameters give an attenuation between a BS and a UE located at a distance of d equal to $-114.5 - 37.19\log_{10}(d)$ dB with d in km and the antennas gains taken into account. The transmit power is $P_{\text{dBm}} = 40$ dBm per BS, the noise power $P_{\text{noise,dBm}} = -101$ dBm, and the radius of the cell $R = 2$ kms. For the symmetric setting, the radius is $R_{\text{sym}} = 1$ km.

A. For the symmetric model

In Fig. 1, the average cell throughputs for the symmetric channel model are shown for the no-interference upper bound as well as when the distributed max-SINR and max-gain scheduler, respectively, are used. The difference between the average rates from the no-interference upper bound and from the max-SINR scheduler is significant but decreases as the number of UEs per cell increases. On the opposite, the average rate achieved with the max-gain scheduler does not seem to converge to the no-interference upper-bound. In fact, the rate difference is plotted in [12] and it is possible to observe clearly that the average rate difference between the no-interference upper bound and the average throughput with a max-SINR scheduler tends to zero, while it tends to a positive constant when max-gain scheduler is used instead.

In Fig. 2, the remaining interference power after scheduling divided by the noise power is plotted for the symmetric channel model. As expected, the interference power with a max-gain scheduler does not decrease as the number of UEs per cell increases since the max-gain scheduler does not take the interference into account, so that the interference power after max-gain scheduling can be used as a reference for the original interference power without scheduling. When max-SINR scheduling is applied, the average interference power decreases monotonically in terms of the number of UEs per cell and seems to tend to zero. Yet, the convergence to zero is extremely slow, as expected theoretically, and for realistic number of UEs per cell, the average interference power remains much larger than the noise power.

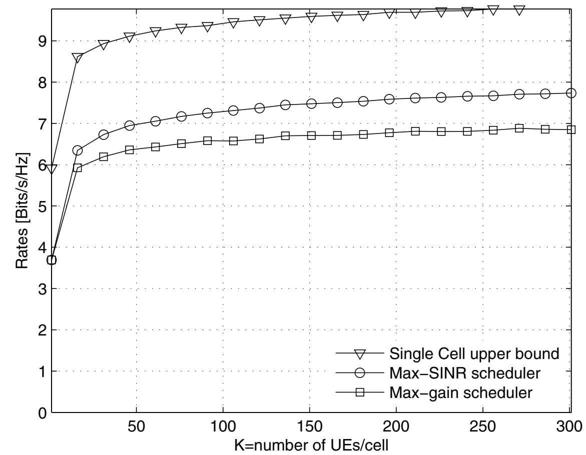

Fig. 1. Average rates in the symmetric model with $R_{\text{sym}} = 1000$m as a function of the number of UEs per cell.

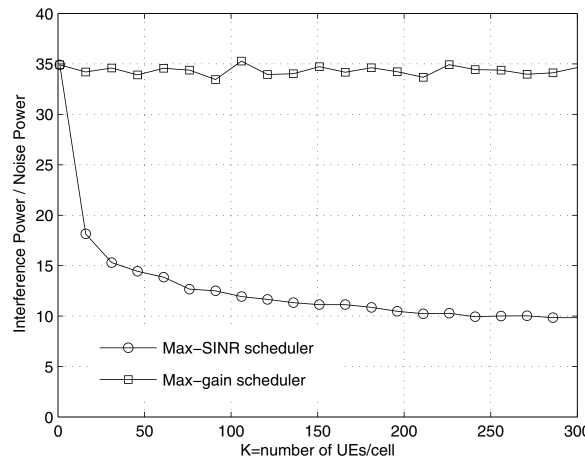

Fig. 2. Average interference power normalized by the noise variance in the symmetric case with $R_{\text{sym}} = 1000$m in terms of the number of UEs per cell.

B. For the asymmetric model

In Fig. 3, the average rates are shown for the asymmetric channel model. The average rate resulting from using the max-gain scheduler is very close to the average rate from the max-SINR scheduler. Moreover, the average difference between the no-interference upper bound and the rate using the distributed schedulers does not decrease as the number of UEs increases

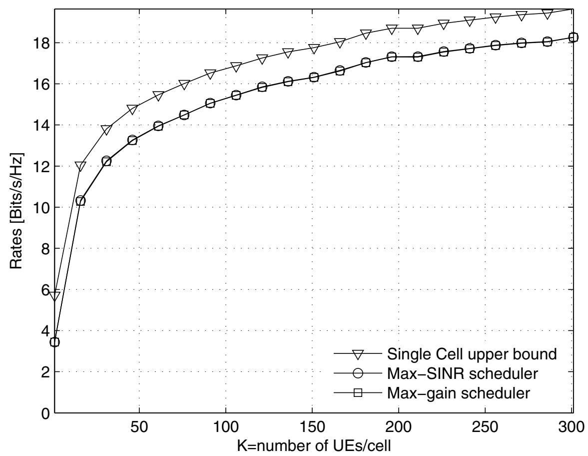

Fig. 3. Average rates in the asymmetric model as a function of the number of UEs per cell.

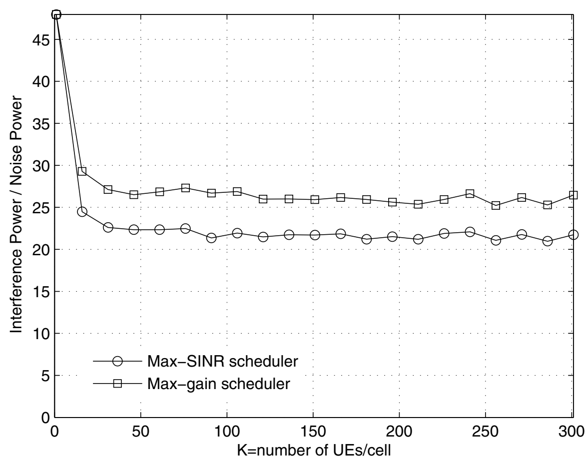

Fig. 4. Average interference power normalized by the noise variance in the asymmetric case in terms of the number of UEs per cell.

and converges instead to a constant. On the opposite to the results in the symmetric channel model, the average rates using the max-SINR and the max-gain scheduling have the same rate of increase in terms of the number of UEs per cell.

This can be put in relation with Fig. 4, where the average interference power after scheduling divided by the noise power is plotted. Indeed, the average interference power after max-SINR scheduler converges for relatively small number of UEs per cell to a value only slightly smaller compared to the original average interference power (which is also the average interference power when using the max-gain scheduler). Thus, the max-SINR scheduler behaves very similarly to the max-gain scheduler. This property can be intuitively understood by the fact that the diversity over the path loss brings a much larger improvement than the diversity over the interference such that the max-SINR scheduler in fact considers practically only the path loss and thus behaves as the max-gain scheduler. The interference power converges in distribution and finding this distribution as well as the limit average interference power after max-SINR scheduling are the subject of ongoing works. Interestingly, the limit average interference power is much larger than the noise level. This can be again linked to the very large SINR increase brought by the path loss diversity.

VI. Conclusion

We have analyzed the asymptotic sum rate in terms of the number of UEs per cell for two channel models: The symmetric model where the path loss is the same for all the UEs and the asymmetric model where the UEs are uniformly distributed in the cell. We have shown that the asymptotic properties of the remaining interference after max-SINR scheduling depend strongly on the channel model. Indeed, the average interference power converges to zero in the symmetric case and to a positive constant in the asymmetric case. The max-SINR scheduler keeps reducing the interference power in the symmetric case, while in the asymmetric case, it performs practically exactly as the scheduler maximizing only the gain of the direct link. By quantifying the rate of convergence for the symmetric model, we make also the observation that the interference power will remain significant at practical number of UEs. This underlines the need for other methods to manage the interference. Finally, fairness is a very critical issue when path loss is taken into account, and the analysis of more fair schedulers for this scenario represents a very interesting problem for further works.

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