Channel Aware Scheduling for Multiple Antenna Multiple Access Channels

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Abstract— **In this paper, we study the optimum transmission strategy of the multiple access channel in a cellular system in which the base station has multiple antennas. Recently, scheduling algorithms incooperating both the physical and data link layer were proposed e.g. in [1], [2], [3] for the multiple antenna case. In this work, we study the scheduling in a SIMO MAC under arbitrary ergodic fading. We assume that the instantaneous channel vector realizations as well as the buffer sizes of all mobiles are known at the base station. The base station performs successive interference cancellation. We propose the optimal scheduling policy. In order to get rid of the time-sharing argument, we define a spatial capacity region in which all rate tupels are achieved by spatial multiplexing only without time-sharing.**

Finally, we connect the capacity region of the SIMO MAC on the physical layer with the stability region of the corresponding queueing system on the data link layer. It is shown that all bit arrival rate vector lying in the capacity region of the SIMO MAC are achievable, too. All theoretical results are illustrated.

I. Introduction

In [4] it was shown that the optimum strategy for maximizing the sum rate of a cellular single-input single-output (SISO) MAC is to allow only the best user to transmit at each time slot. This is not valid for multiantenna systems. The result in [4] has induced the notion of multiuser diversity, i.e. the achievable capacity of the system increases with the number of users. In addition to this, the result in [4] has led to the development of opportunistic downlink scheduling algorithms [5]. In general, the different mobiles have different rate requirements depending on which service they use. The task of fair scheduling algorithms it to guarantee the requirements and to optimize the system throughput [6]. All users share the same frequency band and time slot, thus channelization is uniquely performed in the spatial domain. Unlike single user transmission, multiuser transmission should be jointly optimized with the transmission powers. The transmission powers can be chosen to optimize different criteria functions like the sum capacity, SINR and rate requirements.

Recently, the so called cross-layer design was asked for in [7] in order to optimize the scheduling schemes in future communication systems. This lead to the development of scheduling algorithms which take link layer as well as physical layer parameter into account [3]. In [2], the optimal power allocation and scheduling algorithm for stabilizing a number of queues for fading channel which fulfill the Markovian assumption.

We study a MAC with multiple antennas at the base station. We assume that the base has perfect channel state information. The base performs successive interference cancellation (SIC) in order to achive capacity. From the physical layer view there are two degrees of freedom for scheduling left, namely power allocation and SIC order. In this work, we choose an objective function which is different from the objective functions like sum capacity [8], [9] or the average sum MSE [10]. Following the cross-layer design, the bit-arrival processes from the link-layer at the mobiles is taken into account. The contributions of this work are the following:

1) We trim the familiar capacity region and get rid of the somewhat problematic time-sharing argument. The notion of spatial rate region is introduced which is achievable alone with spatial multiplexing.
2) We propose an optimal scheduling policy which is able to stabilize all bit arrival rate vectors which lie inside the achievable spatial rate region. This scheduling policy has got convincing properties, namely, the optimal permutation order is directly given by the order of bit arrival rates and the remaining power optimization is shown to be convex.

The extension to the MIMO MAC is done in [1] and [11]. The additional choice of transmit covariance matrices complicates the scheduling algorithm.

II. System Model, Preliminaries, First Results and Problem Statement

In our system model in figure (1), we incooperate the data link layer as well as the physical layer. This leads to the application of queuing theory on the link and information theory on the physical layer. There are K users which participate in the SIMO MAC.

The input buffer at the encoder of one user is filled according to a bit-arrival rate q_i [bit/s] of each bulk-arrival process [12] which is given by

$$q_i = \mathbb{E}\left[L_i\right]\lambda_i$$

with average bit-size L_i and packet arrival rate λ_i. The data packets cannot be sent immediatley. As a result, we have a bit arrival rate q_i in front of the encoder. We denote by $a_i(n)$ the number of arrived bits in time interval $[(n-1)T; nT]$.

In general on the physical layer, a number of K users with bit arrival rate vector $\mathbf{q} = [q_1, ..., q_K]$ communicate with a

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base station which is equipped with n antennas at the same time and in the same frequency range. The channel vector realizations of the K users are given by $\mathbf{h}_1, ..., \mathbf{h}_K$ as $1 \times n$ vectors. The received signal vector of size $n \times 1$ at the base station at some time point is given by

$$\mathbf{y} = \sum_{k=1}^{K} \mathbf{h}_k x_k + \mathbf{n}_k$$

with additive white Gaussian noise $\mathbf{n}_k \sim \mathcal{CN}(0, \sigma_n^2 \mathbf{I})$. Each user has an individual power constraint $p_1, ..., p_K$. We define $\rho = \frac{1}{\sigma_n^2}$.

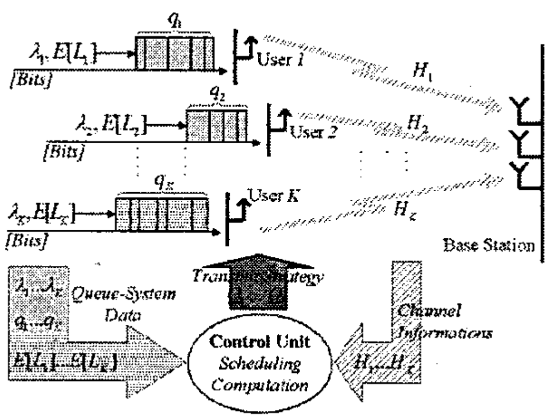

Fig. 1. SIMO MAC model: Cross-layer view of the physical and data link layer and the proposed scheduler

The capacity region of this MAC is given by the set of all rate vectors $\boldsymbol{R}$ which satisfy [13] $\sum_{k \in S} R_k \leq I(\mathbf{y}; (\mathbf{x}_i)_{i \in S} | (\mathbf{x}_i)_{i \notin S})$ $\forall S \subset 1, ..., K$. For the Gaussian MAC with individual power constraints $p_1, ..., p_K$ the capacity region reduces to

$$\mathbf{C}(\mathbf{p}, \mathbf{H}) = \left\{ \mathbf{R} : \sum_{k \in S} R_k \leq \log_2 \det \left(\mathbf{I} + \rho \sum_{k \in S} p_k \mathbf{h}_k^H \mathbf{h}_k \right) \forall S \subset \{1, ..., K\} \right\}. \quad (1)$$

The achievable rate region in (1) depends on the power allocation $\mathbf{p}$ and the channel vector realizations $\mathbf{H} = [\mathbf{h}_1, ..., \mathbf{h}_K]$. The capacity can be achieved by SIC [14]. With SIC the decoding order is important to the different rates of the users. For a fixed user ordering π and power allocation $\mathbf{p}$ we have the rates

$$R_l^{\pi}(\mathbf{p}) = \log_2 \det \left(\mathbf{I} + \sum_{\pi(k) \geq \pi(l)} p_k \mathbf{h}_k^H \mathbf{h}_k \right) - \log_2 \det \left(\mathbf{I} + \sum_{\pi(k) > \pi(l)} p_k \mathbf{h}_k^H \mathbf{h}_k \right).$$

The rate vector $\mathbf{R}^{\pi}(\mathbf{p})$ is then given by $\mathbf{R}^{\pi}(\mathbf{p}) = [R_1^{\pi}(\mathbf{p}), ..., R_K^{\pi}(\mathbf{p})]^T$. We define the S-rate-region (spatial MAC region)

$$\mathbf{S}_{\pi}(\mathbf{H}, \mathbf{p}) = \left\{ \mathbf{R} : R_i \leq R_i^{\pi}(\mathbf{p}) \right\}. \quad (2)$$

Obviously, the S-rate-region is achievable, because for any rate point $\mathbf{R}$ there is a decoding order and power allocation which achieves this rate point. We define the S-rate-region for all power allocations and fixed order π as

$$\mathbf{S}_{\pi}(\mathbf{H}, P) = \bigcup_{\sum_{k=1}^{K} p_k = P} \mathbf{S}_{\pi}(\mathbf{p}, \mathbf{H}) \quad (3)$$

We define the S-rate-region for all possible permutations as

$$\mathbf{S}(H, P) = \bigcup_{\pi} \mathbf{S}_{\pi}(\mathbf{H}, P). \quad (4)$$

Obviously, one can define the ergodic capacities and the ergodic capacity region analoguely to the instantaneous capacity regions, i.e. the ergodic capacity region is given as the convex hull ($\mathcal{CO}(\cdot)$) of all ergodic capacity regions over all power allocations

$$C^{erg}(P) = \mathcal{CO}\left(\bigcup_{\sum_{k=1}^{K} p_k = P} C^{erg}(\mathbf{H}, \mathbf{p}) \right)$$

with ergodic capacity region for fixed power allocation

$$C^{erg}(\mathbf{p}) = \left\{ \mathbf{R} : \sum_{k \in S} R_k \leq \mathbb{E} \log_2 \det \left(\mathbf{I} + \rho \sum_{k \in S} p_k \mathbf{h}_k^H \mathbf{h}_k \right) \forall S \subset \{1, ..., K\} \right\} \quad (5)$$

In order to connect the information theoretic quantities from above with the queueing theory, we need the following definitions:

Definition 1: A scheduling policy is a general mapping from the Cartesian product of the space of K channel vectors $\mathbf{h}_i \in \mathbb{C}^{n_R \times 1}$ and the buffer size vector $\boldsymbol{q} \in \mathbb{R}_+^K$ to the Cartesian product of the space of power allocation vector $\mathbf{p} \in \mathbb{R}_+^K$ and the space of permutations Π

$$\Theta : (\times_{i=1}^{K} \mathbb{C}^{n_R \times 1}) \times \mathbb{R}_+^K \longrightarrow \times_{i=1}^{K} \mathbb{R}_+^K \times \Pi.$$

The function Θ provides tupels with a power allocation $\mathbf{p}$ and a permutation π.

Remark: The scheduling policy Θ depends on the channel realization h and the buffer sizes $\mathbf{q}$. It provides the power allocation $\mathbf{p}$ and permutation π. In order to satisfy a sum power constraint the scheduling policy outputs power allocation with $\sum_{i=1}^{K} p_i = P$.

Definition 2: The system of bit queues at all transmitters $q_1, ..., q_K$ is stable, if for all $i \in \{1, 2, ..., K\}$ holds

$$\lim_{M \to \infty} g_i(M) = 0$$

with the overflow function

$$g_i(M) = \limsup_{t \to \infty} \frac{1}{t} \int_0^t \mathbb{I}_{q_i(\tau) > M} d\tau$$

where the indicator function $\mathbb{I}_E$ takes the value 1 whenever event E is satisfied, and 0 otherwise.

Definition says, that the probability of infinite length of any queue is zero. The next definition characterizes the stability region $\mathcal{D}$ of the SIMO MAC. It is the queueing theoretic counterpart of the capacity region from information theory.

Definition 3: The stability region $\mathcal{D}$ of the SIMO MAC is the set of all bit arrival rate vectors $\boldsymbol{\rho} = [\rho_1, ..., \rho_K]$ such that there exists a scheduling policy Θ which achieves stability of all bit queues for all bit arrival rate vectors in $\mathcal{D}$.

The following theorem characterizes the optimal scheduling policy which achieves the largest possible stability region:

Theorem 1: The spatial SIMO MAC scheduling policy defined by

$$\Theta(\mathbf{H}, \mathbf{q}) = \arg \max_{\mathbf{R} \in \mathbf{S}(\mathbf{H}, P)} \sum_{k=1}^{K} q_k R_k \tag{6}$$

achieves the stability region equal to the ergodic capacity region.

This theorem is proved in [11]. It is further shown by a converse of Fosters criterium [15, Proposition 5.4] that for all vectors outside the ergodic capacity region the system becomes unstable. Therefore, the scheduling policy in 6 is optimal with respect to stability.

Starting from the optimal scheduling policy in 1, we consider the following problem statements which are defined on the basis of the S-rate-region in (4).

Problem 1: For given bit arrival rates $\mathbf{q}$ and channel realization $\mathbf{H}$ find the optimum user decoding order and the optimum power allocation, i.e.

$$S_{opt}(P, \mathbf{q}, \mathbf{H}) = \max_{\mathbf{R} \in \mathbf{S}(\mathbf{H}, P)} \sum_{k=1}^{K} q_k R_k. \tag{7}$$

For small SNR values only one user is allowed to transmit. After solving the first problem, the 'best' user is characterized. In contrast to the case in which the base station has only one antenna [4], the gain by using multiple antennas is that multiple users are allowed to transmit at the same time at sufficient high SNR. The next problem asks about the SNR range in which only one user is transmitting in order to maximize (7).

Problem 2: For given rate requirements $\mathbf{q}$ and channel realization $\mathbf{H}$ find the SNR range in which only one user is allowed to transmit, i.e. $p_{\pi(1)} = P$, $p_{\pi(2)} = ... = p_{\pi(K)} = 0$. Furthermore, we are interested in the shape of the achievable rate regions.

Problem 3: Is the achievable region $\mathbf{S}_{\boldsymbol{\pi}}(\mathbf{H}, P)$ in (3) convex?

III. Optimum User Ordering and Power Allocation

The optimum ordering is characterized in the following

Lemma 1: For given rate requirements $\boldsymbol{q}$ the optimum decoding order π which maximizes $\sum_{k=1}^{K} q_k R_k$ is given by

$$q_{\pi(1)} \geq q_{\pi(2)} \geq ... \geq q_{\pi(K)} > 0. \tag{8}$$

Proof 1: The capacity region $\mathbf{S}(P, \mathbf{H})$ in (4) is a bounded and closed region. Therefore, it exists an optimum rate vector $\mathbf{R}^{opt}$. A optimum user ordering $\boldsymbol{\pi}^{opt}$ and an optimum power allocation $\mathbf{p}^{opt}$ belong to this rate vector $\mathbf{R}^{opt}$. It can be shown that for all fixed individual power constraints $\boldsymbol{p}$ and fixed permutations $\boldsymbol{\pi}$ the achievable rate region $S(\boldsymbol{p}, \mathbf{h}, \boldsymbol{\pi})$ in (1) is a polymatroid [16, Lemma 3.4]. Therefore, it follows by [16, Lemma 3.2] that the maximum of $\sum_{k=1}^{K} q_k R_k$ is attained for the ordering in (8). If $\boldsymbol{\pi}^{opt}$ does not fulfill (8), we apply the [16, Lemma 3.2] to the optimum power allocation $\mathbf{p}$. This leads to a contradiction.

□

Remark: The optimum decoding order is independent from the actual channel vector realizations. The user with the highest rate requirements is decoded last always.

In order to characterize the optimum power allocation, we present the following

Theorem 2: The optimization problem in (7) is concave with respect to the power allocation $\boldsymbol{p}$.

Proof 2: We analyze the objective function with the optimum ordering $\boldsymbol{\pi}^{opt}$

$$\begin{aligned} \sum_{k=1}^{K} q_k R_k &= \sum_{k=1}^{K} q_k \log_2 \det \left(\mathbf{I} + \rho \sum_{l=1}^{k} p_l \mathbf{h}_l^H \mathbf{h}_l \right) \quad (9) \\ &\quad - q_k \log_2 \det \left(\mathbf{I} + \rho \sum_{l=1}^{k-1} p_l \mathbf{h}_l^H \mathbf{h}_l \right) \\ &= \sum_{k=1}^{K} c_k \underbrace{\log_2 \det \left(\mathbf{I} + \rho \sum_{l=1}^{k} p_l \mathbf{h}_l^H \mathbf{h}_l \right)}_{\Phi_k} \quad (10) \end{aligned}$$

with $c_k = q_k - q_{k+1}$ for $1 \leq k \leq K-1$ and $c_K = q_K$. Observe that $c_k \geq 0$ for all $1 \leq k \leq K$. The term Φ_k in (10) is a concave function with respect to the power allocation $\boldsymbol{p}$ for all $1 \leq k \leq K$. The sum of concave functions is concave. This completes the proof.

□

Remark: The result in Theorem 1 is somewhat surprising because the corresponding rate region is neither convex nor concave. The result in Theorem 1 allows to solve the optimization problem in (7) by efficient convex programming methods [17].

In order to characterize the optimum power allocation we define the following coefficients

$$\alpha_k(\mathbf{p}) = c_k \mathbf{h}_k \left(\mathbf{I} + \rho \sum_{l=1}^{K} p_l \mathbf{h}_l^H \mathbf{h}_l \right)^{-1} \mathbf{h}_k^H \tag{11}$$

Furthermore, we define the set of indices for which a given power allocation has entries greater than zero

$$\mathcal{I}(\mathbf{p}) = \{k \in [1...n_T] : p_k > 0\}. \tag{12}$$

The following lemma provides a characterization of the power allocation $\hat{\mathbf{p}}$ which maximizes the objective function in (7) for fixed optimum user ordering $\boldsymbol{\pi}$.

Lemma 2: A necessary and sufficient condition for the optimality of a power allocation $\mathbf{p}$ is

$$\{k_1, k_2 \in \mathcal{I}(\hat{\mathbf{p}}) \implies \alpha_{k_1} = \alpha_{k_2} \text{ and} \tag{13}$$

$$k \notin \mathcal{I}(\hat{\mathbf{p}}) \iff \alpha_k \leq \max_{l \in \mathcal{I}(\hat{\mathbf{p}})} \alpha_l\}. \tag{14}$$

This means that all indices l which obtain some power p_l greater than zero have the same $\alpha_l = \max_{l\in[1...n_T]}$. Furthermore, all other α_i are less or equal to α_l.

Proof 3: The Lagrangian of the power allocation problem in (7) is given by

$$\begin{aligned}\mathcal{L}(\mathbf{p},\mu,\boldsymbol{\lambda}) &= -\sum_{k=1}^{K} c_k \log_2 \det\left(\mathbf{I}+\rho\sum_{l=1}^{K} p_l \mathbf{h}_l^H \mathbf{h}_l\right)\\ &\quad -\sum_{l=1}^{K}\lambda_l p_l - \mu\left(P-\sum_{k=1}^{K}p_k\right). \qquad (15)\end{aligned}$$

The first derivative of the Lagrangian in (15) with respect to $\mathbf{p}_i$ is given by

$$\begin{aligned}\frac{\delta\mathcal{L}(\mathbf{p},\mu,\boldsymbol{\lambda})}{\delta p_i} &= -\rho c_i \mathbf{h}_i\left(\mathbf{I}+\rho\sum_{l=1}^{K}p_l\mathbf{h}_l^H\mathbf{h}_l\right)^{-1}\mathbf{h}_i^H\\ &\quad -\lambda_k+\mu. \qquad (16)\end{aligned}$$

The Karush-Kuhn-Tucker (KKT) conditions for this optimization problem are necessary and sufficient for the optimality of power allocation $\mathbf{p}$ [17]. From (16), we have the following KKT conditions

$$\begin{aligned}\rho c_i\mathbf{h}_i\left(\mathbf{I}+\rho\sum_{l=1}^{K}p_l\mathbf{h}_l^H\mathbf{h}_l\right)^{-1}\mathbf{h}_i^H &= \mu-\lambda_k \;\; 1\le i\le K\\ \lambda_k p_k &= 0 \quad 1\le k\le K\\ \lambda_k &\ge 0 \quad 1\le k\le K\\ \mu &\ge 0\\ p_k &\ge 0 \quad 1\le k\le K\\ P-\sum_{k=1}^{K}p_k &= 0. \qquad (17)\end{aligned}$$

The condition in (14) directly follows from the first KKT condition in (17).

□

The single-user optimality range is characterized in the following

Lemma 3: Assume that the rate requirements are ordered, i.e. $q_1 \ge q_2 \ge ... \ge q_K > 0$. For fixed rate requirements $\mathbf{q}$ and channel realizations $\mathbf{H}$, the SNR range in which only the best user is allowed to transmit is given by

$$\rho \le \frac{q_1||\mathbf{h}_1||^2 - q_2||\mathbf{h}_2||^2}{q_2(||\mathbf{h}_1||^2||\mathbf{h}_2||^2 - ||\mathbf{h}_1^H\mathbf{h}_2||^2)}. \qquad (18)$$

Proof 4: We have assumed that the rate requirements are ordered, i.e. $q_1 \ge q_2 \ge ... \ge q_K > 0$. Hence, the optimum decoding order is given by $\pi = [1,2,...,K]$. We allocate power $P-p$ to the first user and power p to the second user. The sum of the weighted rates is given by

$$\begin{aligned}F(p) &= c_1\log_2\det\left(\mathbf{I}+\frac{(P-p)}{\sigma_n^2}\mathbf{h}_1^H\mathbf{h}_1\right) \qquad (19)\\ &\quad +c_2\log_2\det\left(\mathbf{I}+\frac{(P-p)}{\sigma_n^2}\mathbf{h}_1^H\mathbf{h}_1+\frac{p}{\sigma_n^2}\mathbf{h}_2^H\mathbf{h}_2\right).\end{aligned}$$

with $c_1 = q_1 - q_2$ and $c_2 = q_2$. A necessary and sufficient condition for the optimality of only one user transmitting is given by

$$\frac{\delta F(p)}{\delta p}|_{p=0} \le 0. \qquad (20)$$

The first derivative of $F(p)$ with respect to p is

$$\frac{\delta F(p)}{\delta p} = -\frac{1}{\sigma_n^2}c_1\mathbf{h}_1^H\mathbf{A}\mathbf{h}_1 - \frac{1}{\sigma_n^2}c_2\mathbf{h}_2^H\mathbf{B}\mathbf{h}_2 - \frac{1}{\sigma_n^2}c_2\mathbf{h}_1^H\mathbf{B}\mathbf{h}_1$$

with

$$\mathbf{A} = \left(\mathbf{I}+\frac{(P-p)}{\sigma_n^2}\mathbf{h}_1^H\mathbf{h}_1\right)^{-1}$$

and

$$\mathbf{B} = \left(\mathbf{I}+\frac{(P-p)}{\sigma_n^2}\mathbf{h}_1^H\mathbf{h}_1+\frac{p}{\sigma_n^2}\mathbf{h}_2^H\mathbf{h}_2\right)^{-1}.$$

The first derivative of $F(p)$ with respect to p at the point $p=0$ is given by

$$\begin{aligned}\frac{\delta F(p)}{\delta p}|_{p=0} &= \frac{1}{\sigma_n^2}c_1\mathbf{h}_1^H\mathbf{C}\mathbf{h}_1 - \frac{1}{\sigma_n^2}c_2\mathbf{h}_2^H\mathbf{C}\mathbf{h}_2 -\\ &\quad -\frac{1}{\sigma_n^2}c_2\mathbf{h}_1^H\mathbf{C}\mathbf{h}_1\\ &= -q_1||\mathbf{h}_1||^2 + q_2||\mathbf{h}_2||^2 + q_1\frac{\rho||\mathbf{h}_1||^4}{1+\rho||\mathbf{h}_1||^2}\\ &\quad -q_2\frac{\rho||\mathbf{h}_2^H\mathbf{h}_1||^2}{1+\rho||\mathbf{h}_1||^2}\\ &= -q_1||\mathbf{h}_1||^2 + q_2||\mathbf{h}_2||^2 +\\ &\quad +\rho q_2\left(||\mathbf{h}_1||^2||\mathbf{h}_2||^2 - ||\mathbf{h}_2^H\mathbf{h}_1||^2\right). \qquad (21)\end{aligned}$$

From (21) directly follows the inequality in (18). This completes the proof.

□

IV. Characterization of Rate Regions

For simplicity, we consider the two user case. Let us assume that we decode user one last. Let us solve the rate equation of user one for p_1 and put the resulting $p_1(R_1)$ into the rate of user two. We obtain the rate of user 2 as a function of the rate of user one.

$$\begin{aligned}R_2(R_1) &= \log_2\det\Big(\mathbf{I}+2^{R_1}\left(\frac{\mathbf{h}_1^H\mathbf{h}_1-\mathbf{h}_2^H\mathbf{h}_2}{||\mathbf{h}_1||^2}\right)-\frac{\mathbf{h}_1^H\mathbf{h}_1}{||\mathbf{h}_1||^2}\\ &\quad +\frac{1}{\sigma_n^2}\mathbf{h}_2^H\mathbf{h}_2+\frac{\mathbf{h}_2^H\mathbf{h}_2}{||\mathbf{h}_1||^2}\Big) - R_1. \qquad (22)\end{aligned}$$

It can be shown that the second derivative of $R_2(R_1)$ with respect to R_1 is for some other R_1 smaller than zero and for some R_1 larger than zero. The function is neither convex nor concave.

For the case in which SIC is applied, the problem of the fulfillment of SINR requirements was solved in [18]. This problem differs from the problem in (7). At first, the optimization problem which was solved in [18] is given by

$$\min_{P} \text{ subject to } q_k \le R_k(P) : \mathbf{R}\in\mathbf{S}(\mathbf{H},P)\;\forall 1\le k\le K. \qquad (23)$$

We compare the optimization problems in figure (2) for the two user case.

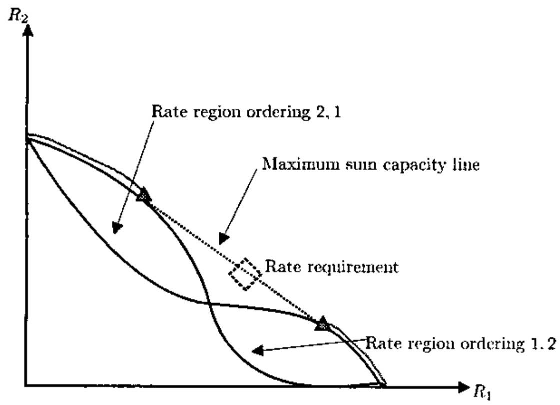

Fig. 2. Illustration of fulfillment of rate requirements vs. proposed optimization vs. time sharing rate region

Assume that the rate requirement point $\Diamond = [q_1, q_2]$ in figure 2 is fixed. The optimization in (23) provides the minimum power which is needed to fulfill the rate requirements. In doing so, the complete spatial rate region is considered (outer solid line in figure 1). In this example, the rate requirement points lies outside of the spatial achievable region and therefore the power has to be increased.

By the rate splitting or time sharing argument the connection line between all achievable points belongs to the achievable region, especially the line at which the sum capacity is achieved (dashed line in figure 1). Hence, we obtain the convex achievable region. In contrast, the proposed optimization problem in (7) does not utilize the time sharing argument. Furthermore, the optimization in (7) does not lead to rigorous fulfillment of rate requirements but to maximized rates with respect to soft weight factors in terms of the users requirements. Starting from requirement vector $[1, 0]$ and decreasing the rate requirement parameter for user one, the rates which solve (7) walk on the solid line up to the sum rate point and jump (for $q_2 > q_1$) to the other side and walk for increasing q_2 to the point $R_1 = 0$. This is illustrated in the pink line.

V. Conclusion

The SIMO MAC scheduling problem based on bit arrival rates from link layer was solved. The optimal scheduling strategy consists of choosing a SIC order of the users and optimal power allocation. The SIC order is determined by the bit arrival rate vector and does not depend on the channel. The power allocation depends on the fading realization and it is a convex optimization problem which can be solved computational efficiently. The proposed scheduling policy is optimal with respect to stability of the input buffer queues, i.e. it stabilizes all bit arrival rate vectors inside the ergodic capacity region.

References

[1] H. Boche and M. Wiczanowski, "Queueing theoretic optimal scheduling for multiple input multiple output multiple access channel," in *International Symposion on Signal Processing and Information Technology (ISSPIT), invited paper*, 2003.

[2] M. J. Neely, E. Modiano, and C. E. Rohrs, "Power allocation and routing in multibeam satellites with time-varying channels," *IEEE/ACM Transaction on Networking*, vol. 11, no. 1, pp. 138–152, February 2003.

[3] E. M. Yeh, "An inter-layer view of multiaccess communications," *Proc. of IEEE ISIT*, 2002.

[4] R. Knopp and P. Humblet, "Information capacity and power control in single-cell multiuser communications," *In Proc. Int. Conf. on Communications*, 1995.

[5] P. Viswanath, D. Tse, and R. Laroia, "Opportunistic beamforming using dumb antennas," *IEEE Transactions on Information Theory*, vol. 48, no. 6, june 2002.

[6] P. Bender, P. Black, M. Grob, R. Padovani, N. Sindhushayana, and A. Viterbi, "CDMA/HDR: A bandwith-efficient high-speed wireless data service for nomadic users," *IEEE Communications Magazine*, vol. 38, no. 7, pp. 70–77, July 2000.

[7] A. J. Goldsmith and S. Wicker, "Design challenges for energy-constrained ad hoc wireless networks," *IEEE Wireless Communications*, vol. 9, no. 4, pp. 8–27, August 2002.

[8] W. Yu, W. Rhee, S. Boyd, and J. M. Cioffi, "Iterative water-filling for gaussian vector multiple-access channels," *Sub. to IEEE Transactions on Inf. Theory*, 2002.

[9] E. Jorswieck and H. Boche, "Rate balancing for the multi-antenna gaussian broadcast channel," *Proceedings of the IEEE International Symposium on Spread Spectrum Techniques and Applications, Prague, Czech Republic, September 2-5,*, 2002.

[10] E. A. Jorswieck and H. Boche, "Transmission strategies for the MIMO MAC with MMSE receiver: Average MSE optimization and achievable individual MSE region," *IEEE Trans. on Signal Processing*, vol. 51, no. 11, pp. 2872–2881, November 2003.

[11] H. Boche and M. Wiczanowski, "Optimal scheduling for high speed uplink packet access - a cross-layer approach," in *Proccedings VTC Spring*, 2004.

[12] L. Kleinrock, *Queueing Systems Volumen 1: Theory*. John Wiley and Sons, New York, 1975.

[13] R. Ahlswede, "Multi-way communication channels," in *Proc. 2nd Int. Symp. Information Theory, Armenian S.S.R*, 1971, pp. 23–52.

[14] M. K. Varanasi and T. Guess, "Optimum decision feedback multiuser equalization with successive decoding achieves the total capacity of the gaussian multiple-access channel," in *Proc. Asilomar Conf. on Signals, Systems and Computers*, 1997, pp. 1405–1409.

[15] S. Assmusen, *Applied Probability and Queues*. Springer-Verlag, New York, 2000.

[16] D. Tse and S. Hanly, "Multi-access fading channels: Part i: Poymatroid structure, optimal resource allocation and throughput capacities," *IEEE Transactions on Information Theory*, vol. 44, no. 7, pp. 2796–2815, November 1998.

[17] S. Boyd and L. Vanderberghe, "Convex optimization," *Course reader for EE364 (Stanford) and EE236 (UCLA), and draft of a book that will be published in*, 2003.

[18] M. Schubert and H. Boche, "Joint 'writing-on-dirty-paper' pre-coding and downlink beamforming," *Proceedings of the IEEE International Symposium on Spread Spectrum Techniques and Applications, Prague, Czech Republic*, September 2-5 2002.