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***Abstract*—We consider the minimization of the energy per bit (or, equivalently, the maximization of the energy efficiency) in a multiple-input single-output (MISO) broadcast channel with rate balancing constraints, i.e., in a multiuser system where certain fixed ratios between the rates of the various users have to be kept. This paper deals with the practically relevant case where the transmit strategy is restricted to simple linear filtering without time-sharing, i.e., sophisticated coding schemes such as dirty paper coding (DPC) are not allowed. Even though the arising optimization problem is non-convex, it can be solved with reasonable complexity in a globally optimal manner using the algorithm proposed in this paper. This globally optimal solution enables us to study the impact of rate balancing constraints on the energy efficiency of a vector broadcast channel in numerical simulations.**

I. INTRODUCTION

With the aim of designing environmentally friendly communication systems with low energy consumption, many researchers have recently focused on the problem of optimizing the energy efficiency of wireless communication systems. Fundamental properties of this problem as well as potential approaches to increase the energy efficiency by improvements on the various abstraction layers of communication systems are summarized, e.g., in [1]–[3].

In addition to works studying the energy efficiency on the circuit level (e.g., [4]–[6]), there is a large variety of papers concentrating on the mathematical optimization of the transmit strategy in abstract models of single-user systems (e.g., [7]–[13]) or multiuser systems (e.g. [14]–[22]). These works have in common that a simple power model consisting of the transmit power and a constant term modeling the circuit power is used, which can be justified by the fact that various more detailed base station power models used in the literature can be transformed to this form [23].

In a multiuser system, the necessity to schedule users on different carriers (e.g., [14]–[18]) and/or to deal with inter-user interference (e.g., [18]–[22]) arises. This makes the energy efficiency optimization of multiuser communication systems qualitatively different from the optimization in the case of a single-user system.

In this work, we consider a single-carrier multiple-input single-output (MISO) broadcast channel, i.e., a multiantenna base station transmits individual data streams to a set of single-antenna users, and the streams can be separated in the spatial domain, but not in the frequency domain. This setting is qualitatively different from the multicarrier, single-antenna broadcast channels considered in [14]–[16], the multicarrier vector broadcast channels with exclusive assignment of carriers to users studied in [17], and the interference channel from [22]. Systems similar to the one under consideration were studied in [18]–[21]. While [18]–[20] propose suboptimal heuristics with low complexity for the energy efficiency optimization in MIMO or MISO broadcast channels, our recent work [21] deals with the globally optimal energy-efficient transmit strategy in MIMO broadcast channels.

When minimizing the energy per bit in a MIMO or MISO broadcast channel without any further restrictions, it might happen that some users are served with a much lower rate than others or are even not served at all. Therefore, the aim of this paper is to not only optimize the energy efficiency of the considered system, but to also guarantee that the resulting per-user rates have certain predefined ratios. In the context of throughput maximization, the optimization with such constraints is usually referred to as *rate balancing* (e.g., [24]–[27]). In connection with the question of energy efficiency, rate balancing constraints were considered in [21], where the globally optimal solution based on DPC and time-sharing was studied.

However, in practice, even approximate DPC as in [28] has prohibitive complexity for online implementation, and time-sharing leads to high signaling overhead (e.g., [26]). For these reasons, a more practical approach to the design of transmit strategies is to allow only linear transmit and receive filters and to exclude the possibility of time-sharing. On the other hand, this restriction usually leads to more involved optimization procedures due to the non-concavity of the rate equations for systems with linear transceivers. In this paper, we will show that the globally optimal linear transmit strategy for energy-efficient rate balancing can, nevertheless, be found with reasonable complexity by means of a combination of existing power minimization algorithms and a monotonic optimization in a single scalar variable.

Monotonic optimization has already been applied to various communication systems (e.g., [29]–[33]). The drawback of approaches based on monotonic optimization is a computational complexity that is exponential in the number of optimization varibables, which is greater than or equal to the number of users in the abovementioned papers. The problem at hand, however, can be reformulated in a way that monotonic optimization needs to be applied only with respect to one variable so that the computational complexity stays polynomial

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in all system parameters. This makes the algorithm practically applicable for real-time implementation, which is not the case for many other algorithms based on monotonic optimization.

Notation: We use $\bullet^{\mathrm{T}}$ for the transpose, $\bullet^{\mathrm{H}}$ for the conjugate transpose, $\mathbf{I}_L$ for the identity matrix of size L, $\mathbf{0}$ for the zero vector, and $\mathbf{1}$ for the all-ones vector. The order relation $\boldsymbol{x} \geq \boldsymbol{y}$ has to be understood element-wise.

II. System Model and Problem Formulation

We consider the downlink of a communication system consisting of a base station equipped with M antennas and K single-antenna user terminals. Assuming frequency flat channels $\boldsymbol{h}_k^{\mathrm{H}}$ and additive circularly symmetric Gaussian noise $w_k \sim \mathcal{CN}(0, \sigma_k^2)$, the data transmission can be described by

$$y_k = \boldsymbol{h}_k^{\mathrm{H}} \sum_{k'=1}^{K} \boldsymbol{u}_{k'} s_{k'} + w_k \tag{1}$$

where $\boldsymbol{u}_{k'}$ are beamforming vectors and $s_{k'} \sim \mathcal{CN}(0,1)$ are circularly symmetric Gaussian data symbols.

According to [34, Section II.B], a set of per-user rates can be achieved in a MISO broadcast channel with linear precoding and a certain sum transmit power $P = \sum_{k=1}^{K} \boldsymbol{u}_k^{\mathrm{H}} \boldsymbol{u}_k$ if and only if the same rates can be achieved in the dual uplink

$$\boldsymbol{y} = \sum_{k=1}^{K} \boldsymbol{g}_k \sqrt{p_k} s_k + \boldsymbol{w} \tag{2}$$

with linear receive processing and the same sum transmit power $P = \sum_{k=1}^{K} p_k$. In (2), p_k are the uplink transmit powers, $\boldsymbol{g}_k = \sigma_k^{-1} \boldsymbol{h}_k$ are the dual uplink channels, and $\boldsymbol{w} \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_M)$ is the noise in the dual uplink. The per-user rates $\boldsymbol{r} = [r_1, \dots, r_K]^{\mathrm{T}}$ achievable by means of linear precoding without time-sharing are then given by

$$r_k(\boldsymbol{p}) = \log_2 \left(1 + p_k \boldsymbol{g}_k^{\mathrm{H}} \left(\mathbf{I}_M + \sum_{k' \neq k} p_{k'} \boldsymbol{g}_{k'} \boldsymbol{g}_{k'}^{\mathrm{H}} \right)^{-1} \boldsymbol{g}_k \right) \tag{3}$$

which is a function of the vector $\boldsymbol{p} = [p_1, \dots, p_K]^{\mathrm{T}}$.

The energy per transmitted bit can be written as

$$E_{\mathrm{b}} = \frac{P_{\text{total}} T}{RT} = \frac{P_{\text{total}}}{R} = \frac{\alpha P + P_c}{\sum_{k=1}^{K} r_k(\boldsymbol{p})} = \alpha \frac{P + c}{\sum_{k=1}^{K} r_k(\boldsymbol{p})} \tag{4}$$

where T is the total transmission time, $R = \sum_{k=1}^{K} r_k(\boldsymbol{p})$ is the sum rate, and the total power P_{total} is expressed as the sum of a scaled version of the transmit power αP and a term $\alpha c = P_c$ modeling the power consumed by the circuit electronics apart from the power amplifier (cf., e.g., [1]). The scalar α is included to account, e.g., for the efficiency of the power amplifier. However, as changing α does not change the structure of the optimizations considered in this paper, we use $\alpha = 1$ for simplicity.

Our aim is to minimize the energy per bit E_{b} subject to rate balancing constraints. In order to avoid dealing with a potential division by zero in (4) (which cannot be the optimal solution anyway), we solve the equivalent problem of maximizing the energy efficiency $\frac{1}{E_{\mathrm{b}}}$ [1] with rate balancing constraints, i.e.,

$$\max_{\boldsymbol{p} \geq \mathbf{0},\, R_0} \frac{\mathbf{1}^{\mathrm{T}} \boldsymbol{r}(\boldsymbol{p})}{\mathbf{1}^{\mathrm{T}} \boldsymbol{p} + c} \quad \text{s.t.} \quad \boldsymbol{r}(\boldsymbol{p}) = R_0 \boldsymbol{\tau} \tag{5}$$

for given positive relative rate targets $\boldsymbol{\tau} = [\tau_1, \dots, \tau_K]^{\mathrm{T}}$. In the special case that all τ_k are equal, it is guaranteed that all users are served with the same rate.

III. Rate Space Formulation

The key to an efficient solution of (5) is a rate-space formulation similar to the one used in [35]. We define

$$\boldsymbol{q}(\boldsymbol{\rho}) = \begin{cases} \boldsymbol{r}^{-1}(\boldsymbol{\rho}) & \text{if } \boldsymbol{\rho} \in \mathcal{R}, \\ [\infty, \dots, \infty]^{\mathrm{T}} & \text{otherwise} \end{cases} \tag{6}$$

where $\mathcal{R} = \{\boldsymbol{r}(\boldsymbol{p}) \mid \boldsymbol{p} \geq \mathbf{0}\}$ denotes the set of rate vectors achievable with finite sum power. According to [35], the inverse function $\boldsymbol{r}^{-1}$ exists and can be evaluated by means of any globally optimal power minimization algorithm for vector broadcast channels with linear precoding and minimum rate constraints. Thus, after testing the feasibility $\boldsymbol{\rho} \in \mathcal{R}$ by checking whether

$$\sum_{k=1}^{K} \left(1 - 2^{-\rho_k}\right) < M \tag{7}$$

as proposed in [36],[1] $\boldsymbol{q}(\boldsymbol{\rho})$ can be evaluated using the algorithm from [37], which is an iterative approach based on a coupling matrix describing the crosstalk between users, or by the fixed point iteration

$$p_k \leftarrow \frac{2^{\rho_k} - 1}{\boldsymbol{g}_k^{\mathrm{H}} \left(\mathbf{I}_M + \sum_{k' \neq k} p_{k'} \boldsymbol{g}_{k'} \boldsymbol{g}_{k'}^{\mathrm{H}} \right)^{-1} \boldsymbol{g}_k} \quad \forall k \tag{8}$$

proposed in [38]. Note that this fixed point iteration converges in very few iterations (typically five to ten) and involves the inversion of an $M \times M$-matrix as computationally most complex operation in each iteration.

Using the function defined above, we can rewrite the optimization in (5) as

$$\max_{\boldsymbol{\rho} \geq \mathbf{0},\, R_0} \frac{\mathbf{1}^{\mathrm{T}} \boldsymbol{\rho}}{\mathbf{1}^{\mathrm{T}} \boldsymbol{q}(\boldsymbol{\rho}) + c} \quad \text{s.t.} \quad \boldsymbol{\rho} = R_0 \boldsymbol{\tau} \tag{9}$$

which enables us to plug the equality constraint into the objective function yielding

$$\max_{R_0} \frac{R_0 \mathbf{1}^{\mathrm{T}} \boldsymbol{\tau}}{\mathbf{1}^{\mathrm{T}} \boldsymbol{q}(R_0 \boldsymbol{\tau}) + c} \quad \text{s.t.} \quad R_0 \geq 0. \tag{10}$$

The new constraint $R_0 \geq 0$ was added to ensure that $\boldsymbol{\rho} = R_0 \boldsymbol{\tau} \geq \mathbf{0}$. This leaves us with a scalar optimization problem with a very simple constraint and an objective function that can be evaluated numerically by efficient algorithms.

[1] If there exist groups of $m \leq \min\{K, M\}$ channel vectors $\boldsymbol{g}_k$ which do not span an m-dimensional subspace of the $\mathbb{C}^M$, additional checks are needed, cf. [36].

IV. GLOBALLY OPTIMAL SOLUTION

As the problem under consideration is nonconvex, it is not guaranteed that local line search methods converge to the global optimum. In order to find the globally optimal solution, we can apply a branch-and-bound line search based on the following monotonicity properties of problem (10).

The numerator is obviously increasing in R_0 since $\mathbf{1}^{\mathrm{T}}\boldsymbol{\tau}$ is a positive constant. In [35], it was shown that $\mathbf{1}^{\mathrm{T}}\boldsymbol{q}(\boldsymbol{\rho})$ is non-decreasing in each component of $\boldsymbol{\rho}$. Therefore, the denominator is non-decreasing in R_0. Having identified the objective function of (10) as the ratio of two monotonic functions, we can apply a modified version of the branch-reduce-and-bound method proposed in [39] for optimization problem involving differences of monotonic functions.

For a function f with

$$f(R_0) = \frac{f_1(R_0)}{f_2(R_0)}, \tag{11}$$

where $f_1(R_0) \geq 0$ and $f_2(R_0) > 0$ are non-decreasing in R_0, the following bounds are valid:

$$f(R_0) \leq U_{[a,b]} = \frac{f_1(b)}{f_2(a)} \quad \forall R_0 \in [a,b], \tag{12}$$

$$\max_{R_0 \in [a,b]} f(R_0) \geq L_{[a,b]} = \frac{f_1(a)}{f_2(a)}. \tag{13}$$

The first bound is due to the monotonicity of f_1 and f_2, and the second bound is an achievability bound.

Given a set $\mathcal{S}$ of intervals $\mathcal{I}$, the highest upper bound $U = \max_{\mathcal{I}\in\mathcal{S}} U_{\mathcal{I}}$ is an upper bound to $f(R_0)$ for $R_0 \in \bigcup_{\mathcal{I}\in\mathcal{S}} \mathcal{I}$. By repeatedly replacing the interval $[a,b] = \operatorname{argmax}_{\mathcal{I}\in\mathcal{S}} U_{\mathcal{I}}$ by two subintervals $\left[a, \frac{a+b}{2}\right]$ and $\left[\frac{a+b}{2}, b\right]$, we eventually achieve $U - L < \epsilon$ for a given error tolerance ϵ, where $L = \max_{\mathcal{I}\in\mathcal{S}} L_{\mathcal{I}}$ is the highest lower bound, i.e., the current best value.

As in [39], convergence of the method can be shown based on the observation that the bounds become tight for $b-a \to 0$ if f_1 and f_2 are continuous, which is called *consistency* in [39]. In our case, it suffices that f_1 and f_2 are continuous at all points R_0 for which $f(R_0) > 0$, which is fulfilled since continuity of $\boldsymbol{r}^{-1}$ was shown in [35].

Even though it follows from [40, Theorem 4] that in the worst case, the number of branch-and-bound iterations needed to find an ϵ-optimal solution is exponential in the number of variables, the computational complexity of the method is polynomial in all system dimensions in our case since the number of variables of the branch-and-bound algorithm is always one, no matter how the system dimensions are chosen.

V. INITIALIZATION

To initialize the algorithm with $\mathcal{S} = \{\mathcal{I}_0\}$, we have to find a bounded initial interval $\mathcal{I}_0 = [a_0, b_0]$ which only contains points feasible for problem (10) and which surely contains the optimizer. The former requirement is easy to fulfill by choosing $a_0 = 0$, but the latter requires some thought.

As was also done in [35], we introduce the single-user rate vector $\boldsymbol{r}_{\mathrm{SU}}(\boldsymbol{p}) = [r_{\mathrm{SU},1}(\boldsymbol{p}), \ldots, r_{\mathrm{SU},K}(\boldsymbol{p})]^{\mathrm{T}}$ with

$$r_{\mathrm{SU},k}(\boldsymbol{p}) = \log_2\left(1 + p_k \boldsymbol{g}_k^{\mathrm{H}} \boldsymbol{g}_k\right) \geq r_k(\boldsymbol{p}) \tag{14}$$

where the inequality holds since interference is neglected in $r_{\mathrm{SU},k}(\boldsymbol{p})$. Moreover, $r_{\mathrm{SU},k}(\boldsymbol{p})$ is increasing in $\boldsymbol{p}$ so that

$$\boldsymbol{r}_{\mathrm{SU}}(\mathbf{1}^{\mathrm{T}}\boldsymbol{q}(\boldsymbol{\rho})\cdot\mathbf{1}) \geq \boldsymbol{r}_{\mathrm{SU}}(\boldsymbol{q}(\boldsymbol{\rho})) \geq \boldsymbol{\rho} \quad \text{for} \quad \boldsymbol{\rho} \in \mathcal{R}. \tag{15}$$

Now let $R_{0,\mathrm{opt}}$ denote the unknown optimizer of (10), and let $\frac{1}{E_{\mathrm{b,init}}} > 0$ denote an achievable value of (10) obtained by plugging in an arbitrary $R_{0,\mathrm{init}} > 0$ such that $R_{0,\mathrm{init}}\boldsymbol{\tau} \in \mathcal{R}$. To find such an $R_{0,\mathrm{init}}$, we compute $\boldsymbol{r}(\boldsymbol{p}_{\mathrm{init}})$ for an arbitrary $\boldsymbol{p}_{\mathrm{init}}$ with positive entries, and we choose $R_{0,\mathrm{init}}$ such that $R_{0,\mathrm{init}}\boldsymbol{\tau} \leq \boldsymbol{r}(\boldsymbol{p}_{\mathrm{init}})$. Then, $P_{\mathrm{opt}} = \mathbf{1}^{\mathrm{T}}\boldsymbol{q}(R_{0,\mathrm{opt}}\boldsymbol{\tau})$ must fulfill

$$\frac{\mathbf{1}^{\mathrm{T}}\boldsymbol{r}_{\mathrm{SU}}(P_{\mathrm{opt}}\mathbf{1})}{P_{\mathrm{opt}} + c} \geq \frac{R_{0,\mathrm{opt}}\mathbf{1}^{\mathrm{T}}\boldsymbol{\tau}}{\mathbf{1}^{\mathrm{T}}\boldsymbol{q}(R_{0,\mathrm{opt}}\boldsymbol{\tau}) + c} \geq \frac{1}{E_{\mathrm{b,init}}}. \tag{16}$$

Note that the left hand side of

$$\frac{\mathbf{1}^{\mathrm{T}}\boldsymbol{r}_{\mathrm{SU}}(P\mathbf{1})}{P + c} \geq \frac{1}{E_{\mathrm{b,init}}} \tag{17}$$

is semistrictly quasiconcave in P since the numerator is concave in P and the denominator is convex in P [41], and it can be easily verified that this left hand side tends to zero for $P \to 0$ and $P \to \infty$. Therefore, equality holds in (17) for two values, which we call $P_{\min}$ and $P_{\max}$, and (17) is fulfilled for $P \in [P_{\min}, P_{\max}]$. For this reason and due to (15), we have $P_{\mathrm{opt}} \in [P_{\min}, P_{\max}]$ and $\mathbf{1}^{\mathrm{T}}\boldsymbol{q}(R_{0,\mathrm{init}}\boldsymbol{\tau}) \in [P_{\min}, P_{\max}]$. From monotonicity and strict concavity of $\mathbf{1}^{\mathrm{T}}\boldsymbol{r}_{\mathrm{SU}}(P\mathbf{1})$, it follows that $P_{\max}$ is the only stable fixed point of the fixed point iteration

$$P \leftarrow E_{\mathrm{b,init}}\mathbf{1}^{\mathrm{T}}\boldsymbol{r}_{\mathrm{SU}}(P\mathbf{1}) - c \tag{18}$$

and $P_{\min}$ is an unstable fixed point. Thus, initialized with $\mathbf{1}^{\mathrm{T}}\boldsymbol{q}(R_{0,\mathrm{init}}\boldsymbol{\tau}) \in [P_{\min}, P_{\max}]$, the iteration (18) converges to $P_{\max}$. This enables us to compute an upper bound $\boldsymbol{r}_{\mathrm{SU}}(P_{\max}\mathbf{1})$ to the unknown optimal rate vector $R_{0,\mathrm{opt}}\boldsymbol{\tau}$. Consequently, $\frac{r_{\mathrm{SU},k}(P_{\max}\mathbf{1})}{\tau_k}$ for arbitrary k delivers a valid upper bound to $R_{0,\mathrm{opt}}$, and we can set the upper boundary b_0 of the initial interval $\mathcal{I}_0 = [a_0, b_0]$ to

$$b_0 = \min_k \frac{r_{\mathrm{SU},k}(P_{\max}\mathbf{1})}{\tau_k}. \tag{19}$$

VI. NUMERICAL RESULTS

We compare the optimal energy per bit with and without rate balancing constraints for systems with linear transceivers and systems with dirty paper coding. The DPC results and the globally optimal linear strategy without rate balancing are computed as described in [21]. For the simulations, we have used 1000 realizations of i.i.d. circularly symmetric Gaussian channel coefficients with zero mean and unit variance.

In Fig. 1, we show results for a vector broadcast channel with $K = 3$ users and $M = 3$ transmit antennas. We plot the optimal energy per bit for various values of the circuit power c in the four cases mentioned before. For rate balancing, we use $\boldsymbol{\tau} = \mathbf{1}$, i.e., all users are served with the same rate.

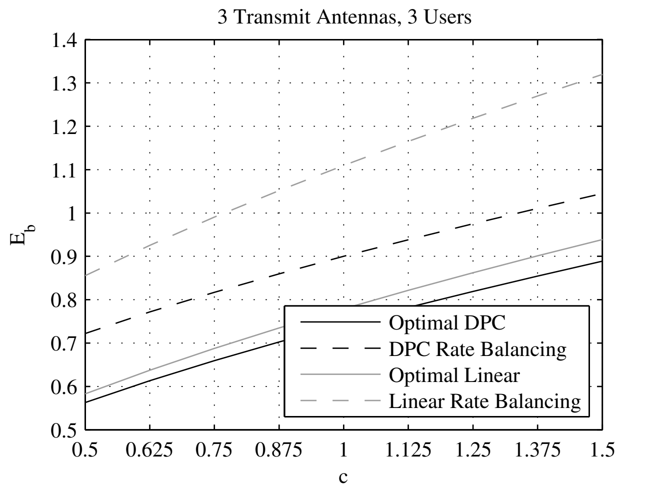

Fig. 1. Energy per bit achieved for various values of the circuit power c.

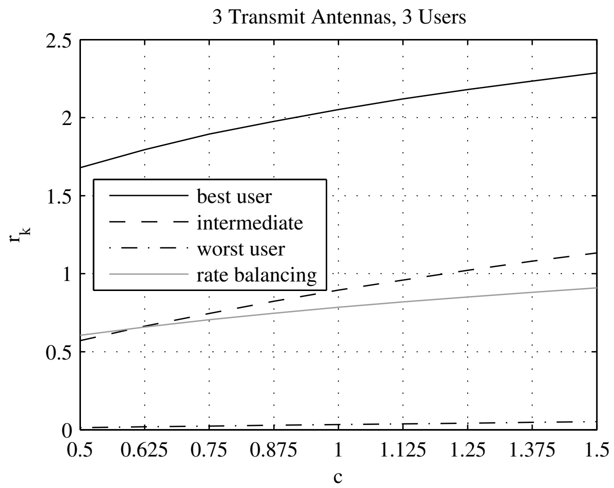

Fig. 2. Per-user rates achieved in the most energy-efficient strategy.

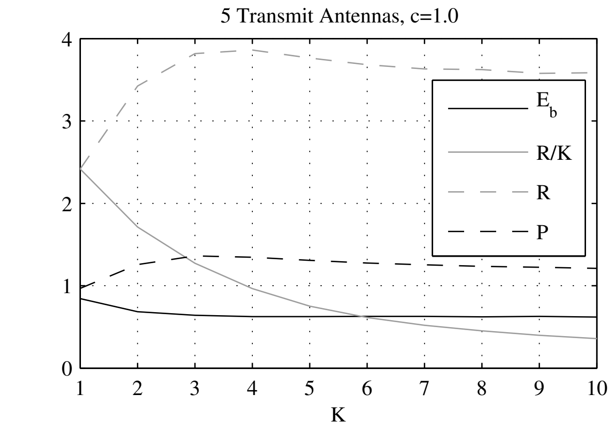

Fig. 3. Optimal energy per bit with rate balancing for various numbers of users K, and corresponding per-user rate $\frac{R}{K}$, sum rate R, and sum power P.

Even though it is clear that introducing rate balancing constraints increases the energy per bit, it is noteworthy that the energy penalty is much more pronounced than in the numerical simulations performed for a MIMO broadcast channel with DPC in our recent work [21]. This can be explained as follows. The optimal energy per bit without rate balancing constraints is achieved by mainly serving users with good channels and disregarding the others. In the MIMO case, the probability that users have very different channel quality decreases due to the additional diversity resulting from multiple receive antennas. This makes it easier to serve all users at the same rate and, thus, reduces the energy penalty for rate balancing.

Clearly, serving mainly the users with good channels is not necessarily the preferred behavior of a communication system, which makes the rate balancing solution interesting despite its worse energy efficiency. To demonstrate this, we include Fig. 2, which shows the average per-user rates for the best, the worst, and the intermediate user when using the optimal energy-efficient linear transmit strategy without rate balancing constraints. The weakest user is served at a rate close to zero on average, and for many channel realizations, this user is even switched off. With rate balancing constraints, all users are served at a rate, which is roughly equal to the rate achieved for the intermediate user in the case without rate balancing.

In Fig. 3, we compare the energy per bit achieved with linear transceivers and rate balancing in a system with $M = 5$ transmit antennas for various numbers of users. Note that the globally optimal linear strategy without rate balancing constraints is not included since, unlike for the rate balancing case, its computation is exponentially complex in the number of users and therefore not feasible for high numbers of users.

We observe that the optimal energy per bit is nearly independent of the number of users in the system apart from the case of a very small number of users K. As long as the spatial multiplexing gain is limited by the number of users in the system, adding an additional user can decrease the energy per bit and increase the sum rate obtained at the most energy-efficient strategy. For high numbers of users $K \geq 5$, the multiplexing gain is limited by the $M = 5$ transmit antennas so that adding new users does not improve the energy efficiency. When further increasing the number of users, inter-user interference increases, and the energy-efficient rate balancing solution operates at a reduced sum rate. The reason is that the sum throughput quickly saturates for high transmit powers in an interference-limited scenario. Thus, it is more energy-efficient to use a lower sum transmit power together with a lower sum rate.

VII. Conclusion

Using a rate-space formulation and existing power minimization algorithms, we have derived an algorithm to compute the globally minimal energy per bit in vector broadcast channels with linear transceivers and rate balancing constraints. Although based on monotonic optimization, the algorithm has polynomial complexity and is, therefore, not only of theoretical interest.

The numerical simulations in this paper reveal that the energy efficiency penalty resulting from rate balancing constraints can be considerable in vector broadcast channels even if the problem of energy-efficient rate balancing is solved in a globally optimal manner. On the other hand, the simulation results also make clear that the energy efficiency optimization without rate balancing leads to very unequal per-user rates and even to users that are not served at all. To find a transmit strategy which is energy-efficient and fair at the same time, it might be necessary to deploy multiple receive antennas.

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