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An Approach to Optimum Joint Beamforming Design in a MIMO-OFDM Multiuser System

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This paper describes a multiuser scenario with several terminals acceding simultaneously to the same frequency channel. The objective is to design an optimal multiuser system that may be used as a comparative framework when evaluating other suboptimal solutions and to contribute to the already published works on this topic. The present work assumes that a centralized manager knows perfectly all the channel responses between all the terminals. According to this, the transmitters and receivers, using antenna arrays and leading to the so-called multiple-input-multiple-output (MIMO) channels, are designed in a joint beamforming approach, attempting to minimize the total transmit power subject to quality of service (QoS) constraints. Since this optimization problem is not convex, the use of the simulated annealing (SA) technique is proposed to find the optimum solution.

Keywords and phrases: multiuser systems, simulated annealing, antenna arrays, MIMO systems, orthogonal frequency division multiplexing, joint beamforming.

1. INTRODUCTION

One of the most important problems of the current and commercial wireless communication systems is that the number of users and the quality of service (QoS) are very limited, including the bit-rate and the bit error rate (BER). These limitations are extremely important since the demands for wireless services are increasing at a very high speed. In this scenario, diversity is a powerful method to increase the number of users and improve the performance. Among the different solutions, the spatial diversity, based on the use of multiple antennas at the transmitter and/or the receiver, has received much attention in last years. Thanks to such techniques, the performance and capabilities of the communication systems can approach the theoretical limits of the wireless channel.

As an illustrative example, we may cite the space division multiple access (SDMA), an advanced medium access protocol that permits the increase of the number of users that can be served simultaneously. In these scenarios, the signals from different users can be separated using array and multichannel processing techniques. Thus, spatial processing can be adopted as a very powerful tool in the so-called multiuser systems. Although currently there are several papers related to this topic, further work is necessary on this research area to fully exploit the capabilities and benefits provided by the use of multiple antennas in multiuser scenarios.

In this paper, a multiuser wireless scenario is considered in which all the “terminals” are assumed to have multiple antennas and, as a consequence, several parallel multiple-input-multiple-output (MIMO) channels arise. In the case of a cellular system, the terminals correspond to both the mobile terminals (MTs) and base stations (BSs). It is also assumed that all of them accede simultaneously to the same frequency radio channel. In this kind of MIMO systems, and depending on the quality and quantity of the channel state information (CSI) at the transmitters, several designs and architectures are possible. We are interested in designing an optimum SDMA strategy that can be used as a comparative framework when designing and evaluating other suboptimal designs for multiuser MIMO systems. According to this objective, we consider that there exists a centralized manager with knowledge of the channel responses between all the terminals in the network. Obviously, this assumption requires the channel to be slowly time varying so that the transmitter can have an accurate channel estimate by means of a feedback channel, for example. Currently, there are several standards in which this assumption is valid. Among them, some examples can be cited, such as the European Wireless Local Area Network (WLAN) HiperLAN/2 [1] and the IEEE 802.11a [2]. These WLANs use orthogonal frequency division multiplexing (OFDM) [3, 4] modulation for the physical layer and, therefore, the use of OFDM by all the terminals has been considered in this paper.

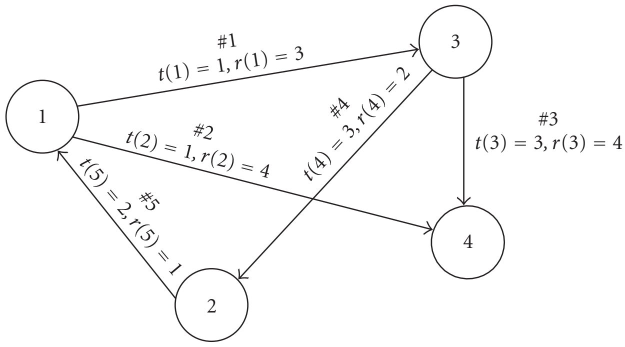
Here, a joint beamforming approach is proposed for the multiuser MIMO-OFDM system, that is, all the transmitters and receivers exploit a beamforming architecture per carrier, instead of using a space-time encoder [5, 6] (the details of the joint beamforming structure are given in Section 2). Obviously, if another architecture different from joint beamforming is used, then an optimum design will be found different from that proposed in this paper. Under this consideration, the receiver is based on a bank of single-user detectors and a joint design of all the transmit beamvectors is carried out by the centralized manager, attempting to minimize the total transmit power. This is done subject to several QoS constraints, which are formulated in terms of the maximum mean BER for each communication or link and, possibly, the maximum transmit power for some MTs. This optimization problem is very difficult to solve, as the constraint set over which the optimization has to be carried out is not convex [7]. As a consequence, in this paper the application of the simulated annealing (SA) technique [8] is proposed, a very powerful heuristic optimization tool able to find the global optimum design even when the mathematical problem is not convex. This is the main difference of this work when compared to other classical techniques found in the literature, in addition to generalizing the already proposed network topologies and design constraints. Most of the other works are based on gradient search (GS) methods or on alternate & maximize (AM) approaches, which may find a suboptimal design since they are not able to handle nonconvex problems. The notation used in this paper is quite general and models many communication systems, including, but not limited to, both the uplink and downlink transmission in cellular networks.

There are some papers in the literature considering similar joint beamforming problems to that presented in this paper. Lok and Wong presented in [9] an uplink multiuser multicarrier code division multiple access (MC-CDMA) system with one antenna at the transmitter side and several antennas at the receiver. The problem consisted in the design of the optimum receiver and the transmit frequency signatures for each user. According to this, the obtained notation and the mathematical optimization problem was shown to be equivalent to the one deduced in our paper. There, the QoS constraints were formulated in terms of a minimum signal-to-noise plus interference ratio (SNIR) for each user instead of a maximum mean BER, as used in this paper, and no constraints were applied regarding the maximum individual transmit powers. The optimization problem was solved by using a GS technique based on the Lagrange multiplier method and the penalty functions.

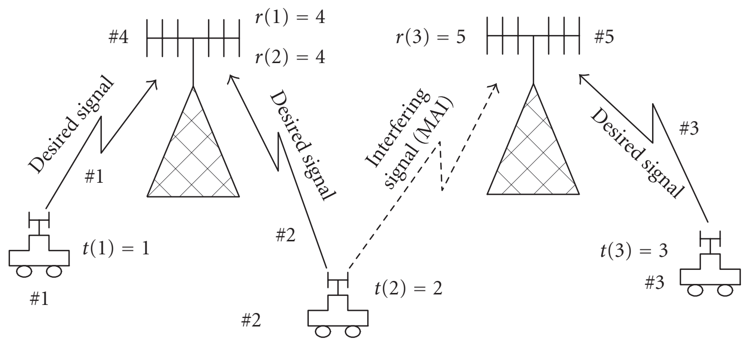
In [10], Wong et al. also considered a multiuser MIMO OFDM system based on joint beamforming. There, the optimization of the transmit beamvectors was based on the application of the AM technique, that is, when designing the beamvector for one user, all the other transmit beamvectors were assumed to be fixed. Once the design was finished, the optimization of the beamvector for another user was performed. This was applied successively until convergence was attained, although the global optimum was not guaranteed to be found, nor were the QoS constrains in terms of a minimum SNIR guaranteed to be fulfilled.

Chang et al. analyzed in [11] the case of an uplink flat fading multiuser MIMO channel, where both the MTs and BS had multiple antennas. Two different optimization problems were considered. In the first one, the minimization of the total transmit power was addressed, forcing the SNIR for each user to be higher than a prefixed value. In the second problem, the objective was to maximize the minimum SNIR subject to a total transmit power constraint. In both cases, no individual transmit power constraint was applied. In that paper, several iterative algorithms were proposed to design the beamvectors, although it was shown that those techniques might find a local suboptimum design instead of the global optimum one due to the nonconvex behaviour of the optimization problem.

There are many other papers that analyze different multiuser systems considering the use of multiple antennas. In [12], an uplink scenario with one BS and several MTs was studied, all of them with multiple antennas. There, the beamforming solution was shown to be optimum in the sense that it achieved the sum capacity for a high number of users, although no QoS could be guaranteed for each user. The same scenario was also considered in [13]. In that paper, the objective was the minimization of the global mean square error (MSE) subject to a transmit power constraint for each MT. The iterative technique was based on the application of the AM algorithm, which might converge to local suboptimum solutions. A multiuser downlink scenario with one multiantenna BS and several single-antenna MTs was analyzed in [14]. There, the global optimum design minimizing the total transmit power subject to minimum SNIR constraints was presented based on the duality between the uplink and downlink scenarios and, furthermore, the conditions for the existence of a feasible solution subject to a total transmit power constraint were deduced. The same problem was analyzed in [15], where the scenario was afterwards extended to the case of several multiantenna BSs and multiantenna MTs, as in our paper. The proposed AM iterative algorithm was shown to converge, but not always to the global optimum solution, once again due to the nonconvexity of the problem. Finally, in [16] the same scenario with several multiantenna BSs and MTs was considered. An iterative AM technique for



(a)



(b)

Figure 1: (a) General configuration for a multiuser system with point-to-point links. In this example, there are 5 simultaneous communications and 4 terminals. (b) Typical configuration in a multiuser MIMO-OFDM scenario with 3 users or communications. There are 5 terminals, where 3 of them are MTs and the other 2 ones are BSs.

the design of the beamformers was presented to minimize the total transmit power subject to QoS constraints in terms of a minimum SNIR for each user, although it was shown that it might converge to a local suboptimum solution. In all these papers, the channel was assumed to be frequency flat, although in our work we have extended the design to the case of a multicarrier modulation in a frequency selective channel.

This paper is structured as follows. In Section 2, the system and signal models for the MIMO-OFDM multiuser scenario are presented, in addition to deducing the expression of the optimal receive beamvectors as a function of the transmit beamvectors. The application of the SA algorithm in order to jointly design all the transmit beamvectors is presented in Section 3, whereas in Section 4 other classical suboptimum designs based on GS and AM algorithms are proposed. Finally, in Sections 5 and 6, some simulation results and conclusions are shown, respectively.

2. SYSTEM AND SIGNAL MODELS

Consider a wireless scenario in which several terminals coexist in the same area. Among these terminals, K communications or links are established and access the common channel at the same time and in the same frequency band. As previously stated, the adopted modulation technique is an N-carriers OFDM. All the terminals in the system are allowed to have multiple antennas and each of them is able to transmit and/or receive. We consider that each communication or link is assigned to two terminals, where one of them is the transmitter and the other one is the receiver.

2.1. MIMO multiuser system and signal models

As it has been stated previously, the system model for the K communications is based on a joint beamforming approach at the transmitter and the receiver, where the beamvectors corresponding to different communications or links are allowed to be different. In this scenario, there exists a set of terminals, where we have not differentiated between BSs and MTs since all the terminals are allowed to transmit and/or receive simultaneously. All the terminals in the system are numbered and the quantity of terminals may be different from the number of established links (see Figure 1). Let $t(k)$ represent the terminal responsible for transmitting the information corresponding to the kth link, whereas $r(k)$ is the terminal receiving this information. In Figure 1, we show some examples of these kinds of systems (a generic example and a more concrete one). Equation (1) represents the signal model for the received snapshot vector for the kth link, that is, it is the received signal model at the $r(k)$th terminal and the nth

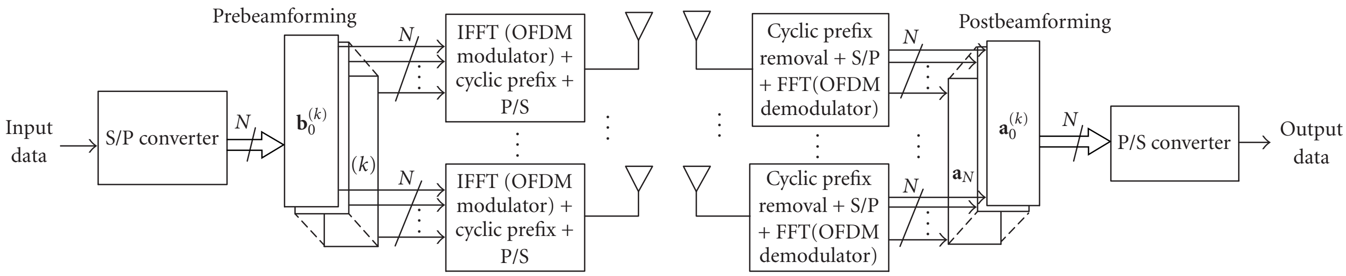


Figure 2: Architecture of the transmitter and the receiver for the kth communication or link based on joint beamforming.

carrier [17] (see Figure 2 in which we represent the architecture of the transmitter and the receiver for the kth link based on joint beamforming):

$$\mathbf{y}_n^{(r(k))}(t) = \sum_{l=1}^{K} \mathbf{H}_n^{(t(l),r(k))}\mathbf{b}_n^{(l)} s_n^{(l)}(t) + \mathbf{n}_n^{(r(k))}(t), \qquad (1)$$

where we have assumed that the length of the cyclic prefix is higher than or equal to the channel order [3]. The size of the vectors $\mathbf{y}_n^{(r(k))}(t)$ and $\mathbf{b}_n^{(l)}$ is equal to the number of antennas at the $r(k)$th and the $t(l)$th terminals, respectively. The transmit beamvector applied to $s_n^{(l)}(t)$ is represented by $\mathbf{b}_n^{(l)}$, where $s_n^{(l)}(t)$ is the transmitted data at the nth carrier during the tth OFDM symbol for the lth link. The transmitted symbols are assumed to have a normalized energy: $\mathbb{E}\{|s_n^{(l)}(t)|^2\} = 1$ ($\mathbb{E}\{\cdot\}$ stands for the mathematical expectation). The matrix $\mathbf{H}_n^{(t(l),r(k))}$ represents the MIMO channel response at the nth carrier between the $t(l)$th and the $r(k)$th terminals. We have also considered that $\mathbf{H}_n^{(i,i)} = \mathbf{0}$, for all i, which means that the ith terminal is not receiving the signal transmitted by itself. Finally, the vector $\mathbf{n}_n^{(r(k))}(t)$ models the contribution of noise plus interferences from outside the system at the $r(k)$th receiver and the nth carrier. The associated covariance matrix is represented by $\mathbf{\Phi}_n^{(r(k))} = \mathbb{E}\{\mathbf{n}_n^{(r(k))}(t)\mathbf{n}_n^{(r(k))^H}(t)\}$, where $(\cdot)^H$ stands for complex conjugate transpose. This signal model is quite general and can easily fit in with many known systems including, but not limited to, the cellular environments, both for uplink and downlink.

2.2. Single-user receiver optimization

In this subsection, the attention is focused on the design of the receive beamvectors. For every link and carrier, a linear combiner $\mathbf{a}_n^{(k)}$ is applied to the set of received samples collected in the snapshot vector $\mathbf{y}_n^{(r(k))}(t)$. The hard estimate of the transmitted symbol $s_n^{(k)}(t)$ for the kth link during the tth OFDM symbol is, therefore, based on a hard mapping applied to the output of the receive beamvector, that is, $\widehat{s}_n^{(k)}(t) = \operatorname{dec}\{\mathbf{a}_n^{(k)^H}\mathbf{y}_n^{(r(k))}(t)\}$. The optimum receive beamvector $\mathbf{a}_n^{(k)}$ is the one maximizing the output SNIR. The expression of the optimum beamvector is widely known and corresponds to the Wiener matched filter [4, 17], which can be formulated as follows assuming that the transmit beamvectors are known:

$$\mathbf{a}_n^{(k)} = \alpha_n^{(k)}\mathbf{R}_n^{(k)^{-1}}\mathbf{H}_n^{(t(k),r(k))}\mathbf{b}_n^{(k)}, \qquad (2)$$

$$\mathbf{R}_n^{(k)} = \mathbf{\Phi}_n^{(r(k))} + \sum_{l=1,\, l\neq k}^{K} \mathbf{H}_n^{(t(l),r(k))}\mathbf{b}_n^{(l)}\mathbf{b}_n^{(l)^H}\mathbf{H}_n^{(t(l),r(k))^H}, \qquad (3)$$

where $\mathbf{R}_n^{(k)}$ is the total interference plus noise covariance matrix seen at the receiver for the kth link, and $\alpha_n^{(k)}$ is a scalar factor that does not affect the SNIR and can be calculated to have an equalized equivalent channel $\mathbf{a}_n^{(k)^H}\mathbf{H}_n^{(t(k),r(k))}\mathbf{b}_n^{(k)} = 1$, $\alpha_n^{(k)} = (\mathbf{b}_n^{(k)^H}\mathbf{H}_n^{(t(k),r(k))^H}\mathbf{R}_n^{(k)^{-1}}\mathbf{H}_n^{(t(k),r(k))}\mathbf{b}_n^{(k)})^{-1}$. As it can be seen in (2), the optimum receive beamvector for the kth link depends on both the transmit beamvector for the same link $\mathbf{b}_n^{(k)}$ and all the other ones $\{\mathbf{b}_n^{(l)}\}_{l\neq k}^{l=1,\ldots,K}$, since the covariance matrix $\mathbf{R}_n^{(k)}$ depends on the transmit beamvectors for all the other links different from k. This produces a coupling effect that makes difficult the optimization of the transmit beamvectors. In the following section, we explicitly focus the attention on the joint design of all the transmitters. By using this design criterion for the receivers, the SNIR at the output of the receive beamformer for the kth link and the nth carrier can be shown to be as follows [17]:

$$\mathrm{SNIR}_n^{(k)} = \mathbf{b}_n^{(k)^H}\mathbf{H}_n^{(t(k),r(k))^H}\mathbf{R}_n^{(k)^{-1}}\mathbf{H}_n^{(t(k),r(k))}\mathbf{b}_n^{(k)}. \qquad (4)$$

Taking into account this result, in OFDM the effective or mean BER is defined as the uncoded BER averaged over all the subcarriers, $\mathrm{BER}^{(k)} = (1/N)\sum_{n=0}^{N-1} \mathcal{Q}(\sqrt{k_m\,\mathrm{SNIR}_n^{(k)}})$, where we have assumed that all the interferences are approximately Gaussian distributed, $\mathcal{Q}(x) = (1/\sqrt{2\pi})\int_x^\infty e^{-t^2/2}dt$, and k_m is a parameter depending on the modulation applied to each subcarrier (for BPSK, $k_m = 2$).

3. SIMULATED-ANNEALING-BASED TRANSMITTER OPTIMIZATION

The last section was devoted to the optimum design of the receive beamvectors assuming that the transmit beamvectors were known, obtaining the closed-form solution corresponding to the Wiener matched filter [4]. Now, the attention is focused on the joint design of all the transmit beamvectors for all the users and all the OFDM carriers.

When designing the transmit beamvectors, an objective function or optimization criterion has to be identified, as well as a set of design constraints. Obviously, a desirable objective is the minimization of the total transmit power, since in wireless networks, high transmit powers imply a shorter lifetime of the MTs. In the case of using several antennas, the power used for transmitting the information symbol corresponding to the nth carrier of the kth user is proportional to $\|\mathbf{b}_n^{(k)}\|^2$. Taking this into account, the total transmit power P_T can be expressed as

$$P_T\left(\{\mathbf{b}_n^{(k)}\}_{n=0,\dots,N-1}^{k=1,\dots,K}\right) = \sum_{k=1}^{K}\sum_{n=0}^{N-1}\left\|\mathbf{b}_n^{(k)}\right\|^2 = \sum_{k=1}^{K}\sum_{n=0}^{N-1}\mathbf{b}_n^{(k)^H}\mathbf{b}_n^{(k)}. \tag{5}$$

Besides the objective function, additional constraints are necessary in order to avoid the trivial solution minimizing the transmit power $\mathbf{b}_n^{(k)} = \mathbf{0}$. In this paper, two kinds of constraints are proposed. The first one refers to the minimum QoS for each communication or link and is mandatory, whereas the other is related to the maximum individual transmit powers for a concrete set of terminals. This set of terminals can be empty and, therefore, the individual transmit power constraints are optional.

(i) *QoS constraints*: these constraints are formulated in terms of the maximum mean BER for each link and can be expressed as follows:

$$\mathrm{BER}^{(k)} \leq \gamma^{(k)}, \quad k = 1,\dots,K, \tag{6}$$

where $\gamma^{(k)}$ is the maximum permitted BER for the kth link and, therefore, is an input parameter of the optimization problem. This formulation generalizes the results presented in [9] for an MC-CDMA system, and in [11, 14, 15, 16] for flat fading channels, where the QoS constraints were formulated in terms of the SNIR instead of the mean BER. In [10, 12, 13], the transmit power was stated to be a prefixed value and the goal was the optimization of the mean quality of all the users in terms of capacity, minimum MSE, and so forth, and therefore, no QoS could be guaranteed for each link. In all cases, the proposed algorithms for the most general scenario, comprising several BSs and MTs with multiple antennas, were shown to be inefficient in the sense that they might find local suboptimum solutions instead of the global optimum one, because of the nonconvex behaviour of the optimization problems.

(ii) *Individual transmit power constraints*: in addition to the QoS constraints, optional constraints can also be included regarding the maximum individual transmit powers for some terminals. This is specially useful for MTs with a power-limited battery in an uplink transmission. Let Υ be the set of terminals to which these constraints are applied. They can be formulated as

$$P_T^{(i)} = \sum_{k=1,\, t(k)=i}^{K}\sum_{n=0}^{N-1}\left\|\mathbf{b}_n^{(k)}\right\|^2 \leq P_{\max}^{(i)}, \quad i \in \Upsilon, \tag{7}$$

where $P_{\max}^{(i)}$ represents the maximum transmit power for the ith terminal. These kinds of constraints have not been considered in any of the works referenced in this paper.

Currently, there exists no closed form solution for this extremely complicated constrained optimization problem, since it is not convex [7]. Although in this case the objective function $\sum_{k=1}^{K}\sum_{n=0}^{N-1}\|\mathbf{b}_n^{(k)}\|^2$ is convex in the optimization variables $\mathbf{b}_n^{(k)}$, the constraint set is not. In order to prove this last statement, we consider the simplest example corresponding to only one user using an OFDM modulation with only one carrier. For this simple case, the maximum BER constraint is equivalent to a minimum SNIR constraint. We assume that $\mathbf{H} = \mathbf{I}$ and that $\mathbf{\Phi}_n = \mathbf{I}$ (we obviate the sub and super indexes to facilitate the notation). According to this, the QoS constraint can be formulated as $\mathbf{b}^H\mathbf{b} \geq \mathrm{SNIR}_{\min}$. This constraint can be represented geometrically as the exterior of a sphere in the variable vector $\mathbf{b}$, which, obviously, is not convex. Due to the nonconvex behaviour of the problem, if a classical GS or AM method is applied to find the optimal design, a local minimum may be found instead of the global optimum in the constraint set. Since we are interested in finding the global optimum design in order to provide a reference system to be used as a comparative framework for other suboptimal designs, we have decided to exploit the SA algorithm. SA is a very powerful heuristic tool able to find the global optimum design even when the objective function or the constraint set is not convex. As stated in the introduction, some previous works have proposed GS techniques, such as in [9], or AM methods [10, 11, 13, 15, 16], among others. The main problem of these techniques is that they are not able to find the global optimum design due to the nonconvex behaviour of the problem, as it was clearly shown in [11] and other works. Besides, in GS and AM techniques, it may be extremely difficult to include any kind of constraint, although in the case of SA this can be done easily, as will be shown later in this section. Specifically, for the case of GS, the constraints are required to be differentiable, although this is not necessary in SA.

In this paper, the existence of a feasible solution is assumed, that is, a collection of transmit beamvectors that satisfies all the constraints simultaneously. In case that a feasible solution does not exist, the algorithm will not converge to any acceptable design.

The SA algorithm has analogies with the annealing of solids in physics and thermodynamics, as has been explained in [8]. The main objective of the annealing process in physics is to obtain a solid with a "perfect" particles arrangement, that is, a perfect structure, so that the energy of the links between these particles is minimized. In order to obtain this perfect structure, initially the solid has to be melted by heating it, that is, until all the particles have total freedom of movement. Once this "hot" state is attained, the temperature has to be lowered until the "perfect" state is obtained, in which the particles have no movement. If the cooling process is done very quickly, the obtained state may be not the one with the minimum energy and, therefore, is not perfect.

If the minimum energy is desired, then the system has to be cooled very slowly, so that the particles have "enough time" to be placed in their optimal positions.

In our problem, in each step of the iterative algorithm there is a collection of transmit beamvectors $\{\mathbf{b}_n^{(k)}\}_{n=0,\dots,N-1}^{k=1,\dots,K}$, which is called the *current solution*. Given the current solution, which is equivalent to a concrete particles arrangement or a state in the annealing process in physics, a *new solution* or collection of beamvectors is proposed. If it is "better" than the original one, then it is retained as the current one. On the contrary, if it is "worse," then the proposed solution is accepted with a certain probability. That means that "worse" solutions may be accepted. This mechanism, which is called *hill climbing*, is extremely important so as to avoid a suboptimal solution or local minimum. The parameter that controls this acceptance probability is the temperature T, as in the case of the annealing in physics. The higher the temperature, the higher the acceptance probability. The temperature is lowered step by step, so that asymptotically, only "better" solutions are accepted and a minimum is approached. The meaning of "better" and "worse" is based on the definition of a cost function $f(\cdot)$ that depends on the transmit beamvectors and is directly related to the total transmit power. This function corresponds to the energy of a state in physics and its minimization is the goal of the annealing process. As in the thermodynamics annealing process, if the temperature is lowered very slowly, the optimum state with the minimum energy, that is, the global minimum of the total transmit power, can be achieved, as desired initially.

Here we provide the description and all the basic ideas of the SA algorithm proposed to solve the already stated optimization problem.

(i) *Cost function definition*:

$$f(\{\mathbf{b}_n^{(k)}\}) = P_T(\{\mathbf{b}_n^{(k)}\}) + \frac{\alpha}{T}\sum_{k=1}^{K}\left(\log\frac{\mathrm{BER}^{(k)}}{\gamma^{(k)}}\right)^{+2} + \frac{\alpha}{T}\sum_{i\in\Upsilon}\left(\log\frac{P_T^{(i)}}{P_{\max}^{(i)}}\right)^{+2}, \tag{8}$$

where $(x)^+ = \max(x,0)$. This cost function, which also depends on the temperature T, is equal to the total transmit power plus a quadratic penalty term. This penalty term takes into account whether the BERs are greater than the maximum permitted ones, and whether the individual transmit powers are greater than those specified. Besides, this penalty term is inversely proportional to the temperature, since in the simulations it has been shown that this rule performs quite well in terms of convergence speed. As T is lowered, the penalty term is increased and, therefore, the acceptance of solutions that do not fulfill the constraints is asymptotically avoided. The parameter α is a proportional factor for the penalty term and its value has been adjusted by simulations to $\alpha = 100$ in order to have good convergence properties. The penalty term is based on relative comparisons of the BERs and the transmit powers with the maximum permitted values by means of the $\log(\cdot)$ function. These kinds of comparisons have been chosen, since it has been observed experimentally that they behave better than absolute comparisons. Note, however, that other kinds of penalty functions could have been used.

(ii) *Proposed solution generation*:

$$\tilde{\mathbf{b}}_n^{(k)} = \mathbf{b}_n^{(k)} + \mathbf{w}_n^{(k)}, \qquad \mathbf{w}_n^{(k)} \sim \mathcal{CN}(\mathbf{0}, \sigma_b^2\mathbf{I}), \quad n = 0,\dots,N-1,\ k = 1,\dots,K. \tag{9}$$

The proposed solutions are generated by applying independent complex circularly symmetric Gaussian noise with variance σ_b^2 to the components of the transmit beamvectors. This noise is used to generate any possible collection of transmit beamvectors in a continuous solution space. Note that there is a difference when compared to the problems for which SA was initially applied, in which the solution space was discrete [8]. The acceptance ratio is monitored for every value of T. In case that it is lower than 0.1 for 5 times, the variance of the Gaussian noise is lowered by means of an exponential profile ($\sigma_b^2 \leftarrow 0.95\sigma_b^2$). This is done in this way as it has been shown experimentally that this rule improves the convergence speed of the algorithm.

(iii) *Probability of acceptance of the proposed solution*:

$$\mathrm{Prob} = \exp\left\{-\frac{1}{T}\left(f(\{\tilde{\mathbf{b}}_n^{(k)}\}) - f(\{\mathbf{b}_n^{(k)}\})\right)^+\right\}. \tag{10}$$

This acceptance probability corresponds to the Metropolis criterion, as described in [8], and is related to the Maxwell-Boltzmann approximation of the Fermi-Dirac distribution describing the energy of an electron in different levels. This criterion was initially used in thermodynamics in order to simulate a thermal equilibrium process. It was shown that, using this criterion, the system could arrive at the minimum possible energy, that is, to the optimum state, if the temperature was lowered slowly. This philosophy was afterwards adopted in the SA algorithm, as shown in this paper, as an efficient criterion to find the global minimum of nonconvex problems.

(iv) *System "cooling"*:

$$T \longleftarrow \beta T, \quad \beta \cong 0.99. \tag{11}$$

As described in this equation, the temperature is lowered very slowly by means of a decreasing exponential rule, as described in [8]. This value of β has been chosen since in the simulations it has been shown to provide good convergence properties, while still guaranteeing that the global optimum solution is attained. As seen in (10), the hotter the system, the higher the acceptance probability. As a consequence, when the temperature is high, most of the proposed transmit beamvectors are accepted, which means they are searching over the range of all the possible spatial

Its objective is to find an initial value of the temperature T, so that the number of accepted solutions is higher than 95%.
(1) $T = 1$, σ_b^2 is set equal to the mean power necessary at the transmitters to attain the required QoS assuming no interference among the users (experimentally it has been shown to have good convergence properties). The initial transmit beamvectors are set equal to all zero vectors.
(2) Propose 100 solutions. Measure the number of nonaccepted solutions N_{na}.
(3) If $N_{na} < 95$, then $T \leftarrow 2T$ and go to step (2). If $N_{na} = 100$, then $T \leftarrow 0.9T$ and go to step (2). In any other case, end.

Algorithm 1: Initialization in the SA algorithm.

They correspond to the application of the SA algorithm.
(1) $L_{ar} = 0$: initialization of the counter corresponding to the number of times that the acceptance ratio is lower than 10%.
(2) Propose 100 solutions. Measure the number of nonaccepted solutions N_{na}. Update the temperature: $T \leftarrow 0.99T$.
(3) If $N_{na} < 10$, then $L_{ar} \leftarrow L_{ar} + 1$. If $L_{ar} = 5$, then $\sigma_b^2 \leftarrow 0.95\sigma_b^2$ and go to step (1). In any other case, go to step (2).
The algorithm finishes when the value of the cost function has stabilized and a minimum has been achieved.

Algorithm 2: Main iterations of the SA algorithm.

directions. When the temperature is lowered, this range is reduced and the accepted transmit beamvectors begin to look for the best spatial directions, that is, for the spatial directions that couple the maximum power towards the desired terminal while reducing the interference towards the other ones.

In the SA algorithm, initially the temperature T has to be high enough so that most of the proposed solutions are accepted. The initial transmit beamvectors are set equal to all zero vectors. Note, however, that the initialization of the beamvectors is not important since in the first iterations most of the proposed solutions are accepted and the variance of the noise to generate and propose new solutions is very high. In this paper, 100 iterations are run for every value of T. As a summary, the main steps of the algorithm are presented and briefly detailed in Algorithms 1 and 2.

4. OTHER CLASSICAL SUBOPTIMUM TECHNIQUES

In the last section, the SA technique has been proposed to find the global optimum design of the stated constrained optimization problem. In this section, we present two alternative algorithms based on the GS and the AM methods.

4.1. *Lagrange-gradient search transmitter optimization*

A classical approach different from the SA consists in the utilization of a gradient technique, although, as it has been already said, the main drawback of this family of algorithms is that they may converge to local suboptimum designs. In order to compare the SA with other classical approaches, in this section we propose an iterative gradient technique based on the classical Lagrange multipliers method and the quadratic penalty term [9, 18]. This technique is based on the definition of a Lagrangian expression $\mathcal{L}$. When formulating the Lagrangian expression and the penalty term, we take into account the fact that the optimal solution implies that the QoS are fulfilled with equality. Under this assumption, that can be shown easily, the Lagrangian expression can be formulated as

$$\mathcal{L} = P_T + \lambda\left[\sum_{j=1}^{K}\left(\log\frac{\mathrm{BER}^{(j)}}{\gamma^{(j)}}\right)^2 + \sum_{i\in\Upsilon}\left(\log\frac{P_T^{(i)}}{P_{\max}^{(i)}}\right)^{+2}\right]. \quad (12)$$

The equations that show how to update the transmit beamvectors and the penalty factor λ correspond to the well-known gradient descent and ascent techniques, as also used in [9]

$$\begin{aligned}\mathbf{b}_n^{(k)} &\longleftarrow \mathbf{b}_n^{(k)} - \mu\nabla_{\mathbf{b}_n^{(k)H}}\mathcal{L},\\ \lambda &\longleftarrow \lambda + \mu\left[\sum_{j=1}^{K}\left(\log\frac{\mathrm{BER}^{(j)}}{\gamma^{(j)}}\right)^2 + \sum_{i\in\Upsilon}\left(\log\frac{P_T^{(i)}}{P_{\max}^{(i)}}\right)^{+2}\right],\end{aligned} \quad (13)$$

where μ is the step size parameter that has to be adjusted to cope with the tradeoff between the convergence speed and the convergence itself. The initial beamvectors can be calculated assuming that there is no interference between users, as shown in [10, 17]. The initial value for the penalty factor λ is set equal to 0. Here, the necessary expressions to calculate the gradient $\nabla_{\mathbf{b}_n^{(k)H}}\mathcal{L}$ are provided. In order to facilitate the notation, we assume an uplink scenario with several MTs transmitting to a single BS, which is responsible for the detection of the symbols transmitted by all the MTs. The modulation of the subcarriers is BPSK. In this scenario, the matrix $\mathbf{H}_n^{(k)}$ represents the response of the MIMO channel at the nth carrier between the kth MT and the BS. The extension to other kinds of scenarios is quite simple by using very similar expressions. The function $\delta_\Upsilon(k)$ is defined as $\delta_\Upsilon(k) = 1$, $k \in \Upsilon$, and $\delta_\Upsilon(k) = 0$, $k \notin \Upsilon$:

$$\begin{aligned}\nabla_{\mathbf{b}_n^{(k)H}}\mathcal{L} = \mathbf{b}_n^{(k)} &+ 2\lambda\sum_{j=1}^{K}\frac{1}{\mathrm{BER}^{(j)}}\left(\log\frac{\mathrm{BER}^{(j)}}{\gamma^{(j)}}\right)\nabla_{\mathbf{b}_n^{(k)H}}\mathrm{BER}^{(j)}\\ &+ \delta_\Upsilon(k)2\lambda\frac{\mathbf{b}_n^{(k)}}{P_T^{(k)}}\left(\log\frac{P_T^{(k)}}{P_{\max}^{(k)}}\right)^{+}.\end{aligned} \quad (14)$$

(1) Initialization: set all the transmit beamvectors proportional to the maximum eigenvectors of the matrices $\mathbf{H}_n^{(t(k),r(k))^H}\mathbf{\Phi}_n^{(r(k))^{-1}}\mathbf{H}_n^{(t(k),r(k))}$, that is, without taking into account the interferences from other users. Calculate the power allocation (either uniform or maxmin) to satisfy the QoS constraints.
(2) Repeat until convergence.
  (i) Calculate all the covariance matrices (see (3)).
  (ii) Calculate all the transmit beamvectors as the maximum eigenvectors of $\mathbf{H}_n^{(t(k),r(k))^H}\mathbf{R}_n^{(k)^{-1}}\mathbf{H}_n^{(t(k),r(k))}$ and the corresponding power allocation satisfying the QoS constraints.

Algorithm 3: Application of the AM algorithm.

The expression of $\nabla_{\mathbf{b}_n^{(k)^H}}\mathrm{BER}^{(j)}$ depends on j. Firstly, we give the expression for the case $j = k$:

$$\begin{aligned}\nabla_{\mathbf{b}_n^{(k)^H}}\mathrm{BER}^{(k)} &= -\frac{1}{N\sqrt{2\pi}}\exp\left(-\mathrm{SNIR}_n^{(k)}\right)\\ &\quad\times\frac{1}{\sqrt{2\,\mathrm{SNIR}_n^{(k)}}}\mathbf{H}_n^{(k)^H}\mathbf{R}_n^{(k)^{-1}}\mathbf{H}_n^{(k)}\mathbf{b}_n^{(k)}.\end{aligned}\tag{15}$$

For the case $j \neq k$, the expression is as follows, where the matrix inversion lemma has been used:

$$\begin{aligned}\nabla_{\mathbf{b}_n^{(k)^H}}\mathrm{BER}^{(j)} &= -\frac{1}{N\sqrt{2\pi}}\exp\left(-\mathrm{SNIR}_n^{(j)}\right)\\ &\quad\times\frac{1}{\sqrt{2\,\mathrm{SNIR}_n^{(j)}}}\nabla_{\mathbf{b}_n^{(k)^H}}\mathrm{SNIR}^{(j)},\\ \nabla_{\mathbf{b}_n^{(k)^H}}\mathrm{SNIR}^{(j)} &= \frac{\mathbf{H}_n^{(k)^H}\mathbf{R}_n^{(j,k)^{-1}}\mathbf{H}_n^{(k)}\mathbf{b}_n^{(k)}}{\left(1+\mathbf{b}_n^{(k)^H}\mathbf{H}_n^{(k)^H}\mathbf{R}_n^{(j,k)^{-1}}\mathbf{H}_n^{(k)}\mathbf{b}_n^{(k)}\right)^2}\\ &\quad\times\left|\mathbf{b}_n^{(j)^H}\mathbf{H}_n^{(j)^H}\mathbf{R}_n^{(j,k)^{-1}}\mathbf{H}_n^{(k)}\mathbf{b}_n^{(k)}\right|^2\\ &\quad-\frac{\mathbf{b}_n^{(j)^H}\mathbf{H}_n^{(j)^H}\mathbf{R}_n^{(j,k)^{-1}}\mathbf{H}_n^{(k)}\mathbf{b}_n^{(k)}}{1+\mathbf{b}_n^{(k)^H}\mathbf{H}_n^{(k)^H}\mathbf{R}_n^{(j,k)^{-1}}\mathbf{H}_n^{(k)}\mathbf{b}_n^{(k)}}\\ &\quad\times\mathbf{H}_n^{(k)^H}\mathbf{R}_n^{(j,k)^{-1}}\mathbf{H}_n^{(j)}\mathbf{b}_n^{(j)},\\ \mathbf{R}_n^{(j,k)} &= \mathbf{\Phi}_n+\sum_{l=1,\,l\neq j,\,l\neq k}^{K}\mathbf{H}_n^{(l)}\mathbf{b}_n^{(l)}\mathbf{b}_n^{(l)^H}\mathbf{H}_n^{(l)^H}.\end{aligned}\tag{16}$$

As previously stated, one of the main drawbacks of the GS technique is that a local suboptimum design may be found. This could be solved by using different initial sets of beamvectors, selected randomly. Note, however, that this increases the computational load and does not guarantee a successful result.

4.2. *Alternate & maximize transmitter optimization*

Finally, another classical solution that has been used previously by many authors in papers such as [10, 13, 15, 16], among others, is the AM algorithm. In our problem, the SNIR for a concrete user and carrier depends, not only on the beamvector for the considered user, but also on all the transmit beamvectors for all the other users through the covariance matrix, as shown in (3) and (4). The AM algorithm is an iterative technique, so that in each step the beamvectors associated to a concrete user are designed assuming that the beamvectors of all the other users are fixed, that is, assuming that the noise plus interferences covariance matrix is known. Obviously, when a beamvector for a user is designed, the covariance matrix for the other users change and, therefore, the technique has to be applied iteratively until convergence is attained.

In this subsection, we provide the description of an AM algorithm in which we only take into account the QoS constraints, but not the individual transmit power constraints, since their inclusion in the algorithm is extremely difficult. In each step, the optimum transmit beamvector maximizing the SNIR corresponds to the eigenvector associated to the maximum eigenvalue of the matrix $\mathbf{H}_n^{(t(k),r(k))^H}\mathbf{R}_n^{(k)^{-1}}\mathbf{H}_n^{(t(k),r(k))}$ (see a complete proof of this in [10, 17]). Besides this, an adequate power allocation among the carriers of the OFDM modulation has to be calculated, so that the QoS constraint in terms of the maximum BER is fulfilled. In this paper, we have used two different power allocation policies: the uniform and the maxmin techniques, as completely described in [17].

Algorithm 3 shows the main steps of the AM technique, including the beamvectors initialization. The main disadvantage of this algorithm, as commented previously and in papers such as [13, 15, 16], is that the obtained solution may be a local suboptimum design instead of the global optimum one, since the optimization problem is not convex. Besides, there is no a priori guarantee of convergence. A possible solution would consist in using different random initializations for the transmit beamvectors. Note, however, that this is an ad hoc procedure that does not control and guarantee that the global optimum design is obtained.

5. SIMULATION RESULTS

In this section, we simulate an uplink scenario with 3 MTs and 1 BS. The OFDM modulation consists of $N = 16$ carriers and both MTs and BS have 5 antennas. The QoS constraints in terms of the mean BER are 10^{-3}, 10^{-3}, and 10^{-2} and $\alpha = 100$, as stated in Section 3. The noise is assumed to be white both in the time and space domains, with a normalized variance equal to 1, that is, $\mathbf{\Phi}_n^{(r(k))} = \mathbf{I}$. The simulations and algorithms are applied to a single realization of the multiple OFDM-MIMO channels, although we do not provide the numerical expressions of the channel matrices for the sake of clarity.

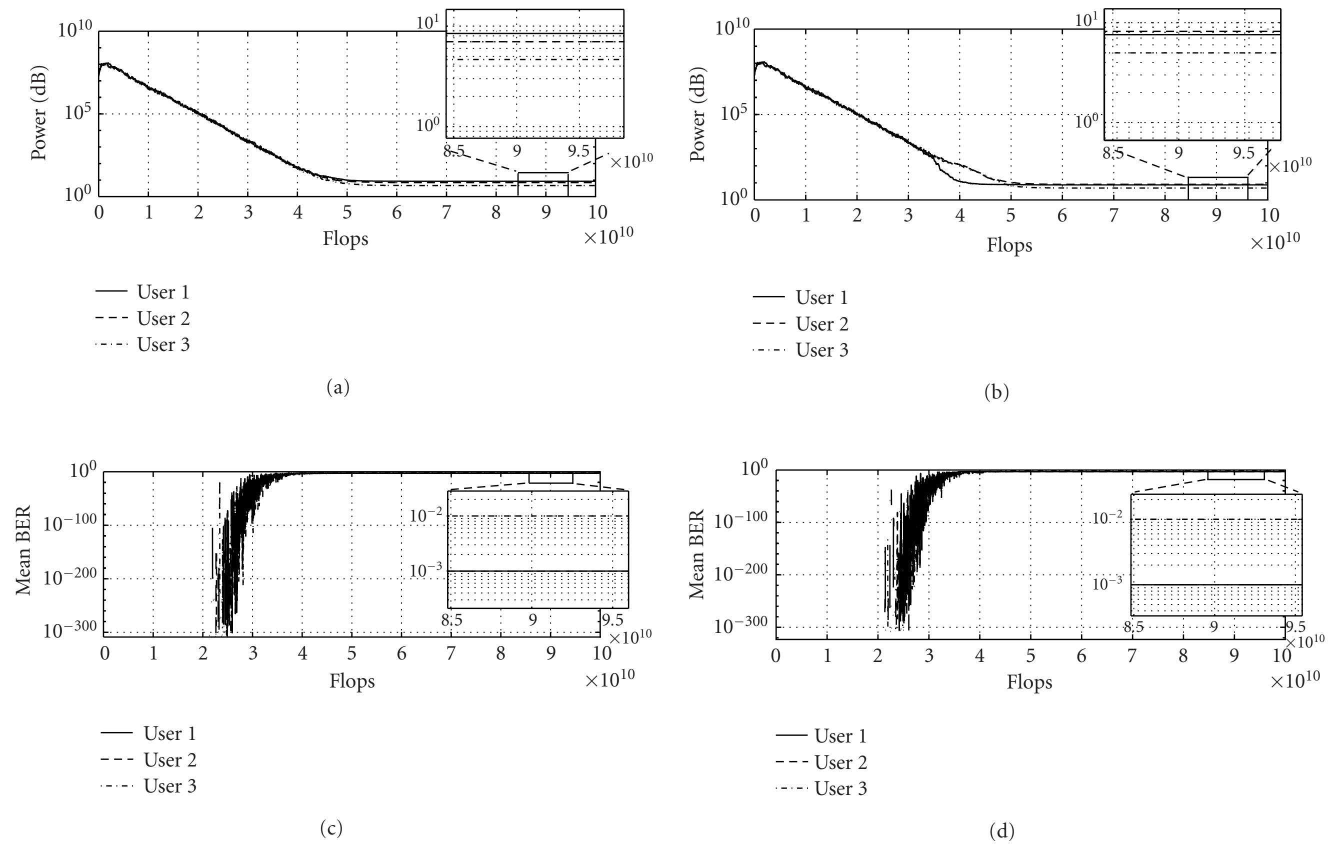


Figure 3: Powers of the MTs for SA in scenario 1. (b) Powers of the MTs for SA in scenario 1 including a power constraint in MT1. (c) BERs of the MTs for SA in scenario 1. (d) BERs of the MTs for SA in scenario 1 including a power constraint in MT1.

In the first scenario, it is assumed that the path loss is very similar for all the users. In Figures 3a and 3c, we show the evolution of the powers allocated to the three users and the mean BERs as the iterations of the SA algorithm run, concluding that the proposed technique is able to find a design fulfilling the constraints when no individual power restrictions are applied. The optimum power corresponding to the first user is 8.45 W, and the total power is 20.1 W. If a power constraint is applied to the first user is equal to 8 W, then the results are those shown in Figures 3b and 3d. The main conclusion is that, in this case, the SA algorithm allocates 7.6 W to the first user, whereas the other ones increase their corresponding power consumption. As it is also shown, the global transmit power has increased up to 20.8 W. This increase of the total transmit power is normal, as in the second example, a more restrictive constraint has been applied and, therefore, the optimization has to be carried out over a more limited set of transmit beamvectors fulfilling the constraints.

In Figure 4, a set of results are presented for the case of a scenario in which the third user has a path loss with respect to the first two users equal to 12 dB. In this example, no individual transmit power constraint has been considered. Figures 4a and 4c corresponds to the application of SA, whereas Figures 4b and 4d corresponds to the GS algorithm with a μ parameter, that is, the step size, equal to 0.001. The main conclusion is that with the same computational load or number of floating point operations, the SA algorithm can fulfill the constraints, whereas the GS technique decreases importantly the convergence speed as the solution approaches these constraints. This is because the penalty terms applied in the Lagrangian expression (12) are quadratic and, therefore, when calculating the derivatives in a point near from the fulfillment of the constraints, these derivatives tend to zero. Simulations concerning the application of the AM algorithm have also been done for two different power allocation techniques, uniform and maxmin [17]. From the simulations, it is concluded that AM has a high convergence speed. Table 1 shows a summary of the results for all the techniques. The conclusion is that GS does not find a solution fulfilling the constraints, whereas AM does not have this problem, as in the case of SA. The main drawback is that the necessary transmit power is higher for AM than for SA, concluding that a local suboptimum design has been found. Indeed, and as explained in [15], the nonconvexity and the number of local minima increases as more BSs and MTs are coexisting in the same area.

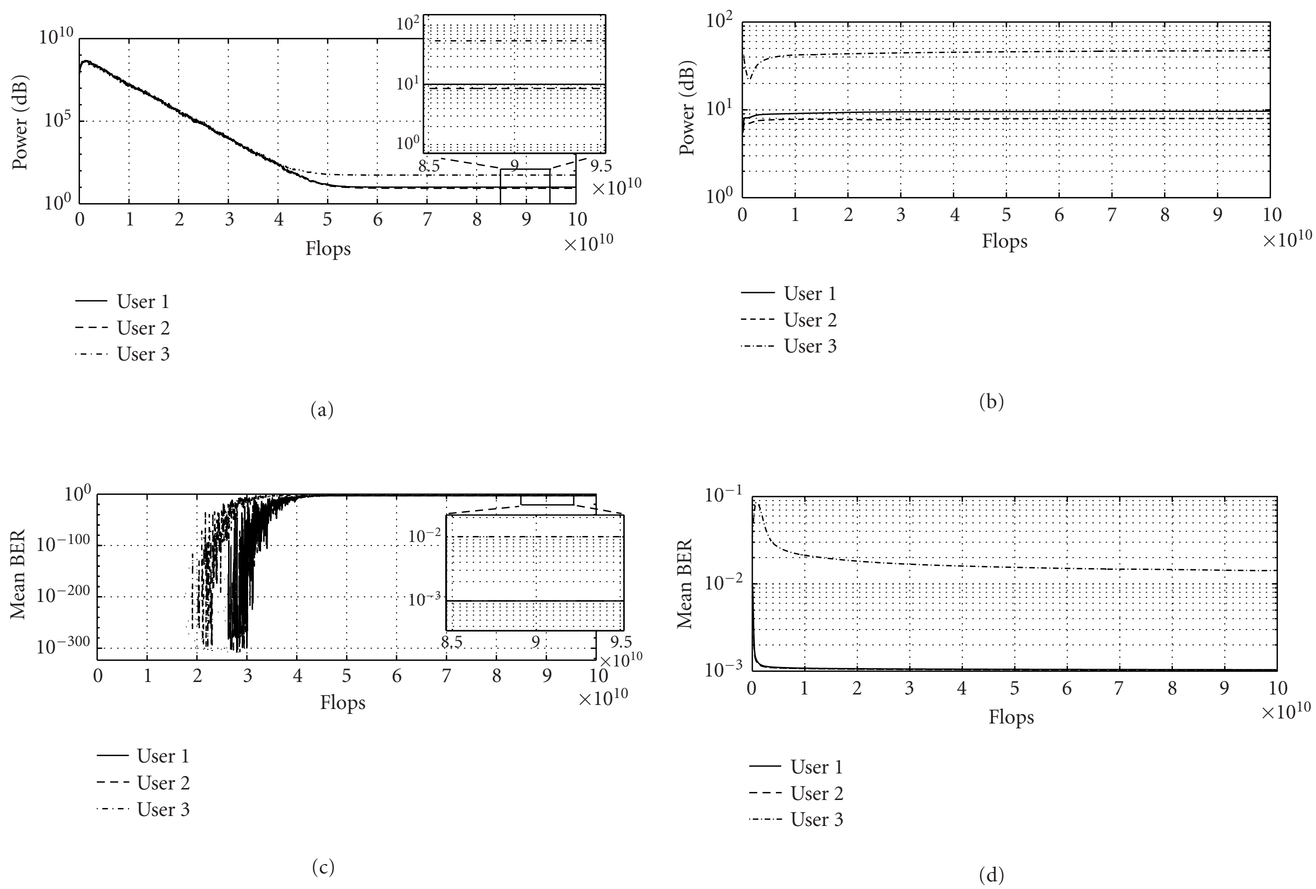


Figure 4: (a) Powers of the MTs for SA in scenario 2. (b) Powers of the MTs for GS in scenario 2. (c) BERs of the MTs for SA in scenario 2. (d) BERs of the MTs for GS in scenario 2.

Table 1: Power and BER for SA, GS, and AM.

	MT 1 power	MT 2 power	MT 3 power	Total power	MT 1 BER	MT 2 BER	MT 3 BER
SA	10.2 W	8.7 W	54.5 W	73.4 W	10^{-3}	10^{-3}	10^{-2}
GS	9.6 W	8 W	46.5 W	64.1 W	$1.01 \cdot 10^{-3}$	$1.01 \cdot 10^{-3}$	$1.42 \cdot 10^{-2}$
AM-maxmin	8.3 W	6.8 W	63.6 W	78.7 W	10^{-3}	10^{-3}	10^{-2}
AM-uniform	9.1 W	7.9 W	65.5 W	82.5 W	10^{-3}	10^{-3}	10^{-2}

6. CONCLUSIONS

As a general conclusion, in this paper a MIMO-OFDM multiuser system based on a joint beamforming approach has been proposed. The objective was the joint design of the beamvectors associated to all the established communications or links, taking as the optimization criterion the minimization of the total transmit power subject to maximum mean BER and individual transmit power constraints. It has been shown that this problem is not convex and, therefore, the application of the SA technique has been proposed, in addition to classical GS and AM methods. The SA has been shown to be able to find the optimum solution and, therefore, the obtained design may be used as a comparative framework for other suboptimum solutions. Other classical techniques, such as GS and AM, also presented in this paper, may have problems related to the convergence speed and the fact that local suboptimum designs may be found. Besides, GS and AM cannot always include every kind of constraint, whereas in SA this can be easily done by using adequate penalty functions.

Although SA has been shown to be a powerful tool to cope with the optimization of nonconvex problems, such as the one presented in this paper, there exist other heuristic approaches that should be also considered as possible strategies. Among these techniques, some examples can be given, such as the genetic algorithms (GA) [19] or taboo search (TS) approaches. In both cases, the techniques are based on a random generation of possible solutions, such as in the SA algorithm, and are also able to find the optimum solution, even if the problem is not convex. The main difference between SA and the GA-TS strategies is that the last two techniques transform the solution space, that is, the set of possible transmit beamvectors, into a space composed of "bits" by means of an encoding process. Once this transformation has been performed, the optimization problem is solved in this new transformed solution space. Finally, the solution in terms of transmit beamvectors should be found by transforming or decoding the solution in the coded space. Further work is to be done on the application of these techniques in order to evaluate whether the computational load of the optimization problem can be decreased while still guaranteeing that the global optimum design is found.

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