Energy-Efficient Resource Allocation Based on Interference Alignment in MIMO-OFDM Cognitive Radio Networks

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Abstract. In this paper, we propose an energy-efficient interference alignment (IA) based resource management algorithm for multi-input multi-output (MIMO) orthogonal frequency division multiplexing (OFDM) cognitive radio (CR) systems. The proposed algorithm provides the secondary users (SUs) with the opportunity for underlay sharing of the primary system spectrum. The proposed algorithm ensures the quality-of-service (QoS) of the primary system by guaranteeing the minimum transmission rate. The problem is formulated as a mixed-integer non-convex optimization problem, in which the objective is to maximize the energy efficiency, and the constraints are the per-user power budget and QoS demand of the primary system. To tackle mixed-integer and non-convexity nature of the problem, we propose a sub-optimal energy-efficient algorithm through two successive steps. The first step schedules the subcarriers among the SUs based on IA while the second step iteratively allocates the power based on Dinkelbach's scheme. Simulations reveal that the proposed algorithm achieves significant improvement in the energy efficiency compared to the traditional spectrum-efficient algorithm.

Keywords: Cognitive radio · Interference alignment · Resource allocation · Energy efficiency · MIMO · OFDM

1 Introduction

Cognitive radio (CR) is considered as a promising technology that overcomes the scarcity and the underutilization of the spectrum [1]. In this context, the secondary users (SUs) are allowed to share the same spectrum bands with the primary users (PUs) provided that the quality of service (QoS) of the PUs is guaranteed. Recently, interference alinement (IA) is merged with CR as an efficient interference management technique in order to achieve optimal utilization of the system resources. IA is a cooperative transmission approach that achieves an optimal sum-rate for K-user interference channels at high signal-to-noise-ratio (SNR). IA is performed by aligning the interference signals from the undesired transmitters in certain subspaces, termed as interference subspaces, and the desired signal in the other subspaces, termed as interference-free subspaces [2],[3].

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Energy efficiency gains much of interest nowadays due to the rapidly increasing cost of energy [4,5]. The ever-increasing data-rate demands require energy-efficient transmissions in order to prolong the battery lifetime of wireless devices. However, energy-efficient based IA resource allocation in multi-input multi-output (MIMO) CR systems is rarely addressed in the literature, where many research works considered the problem of IA based resource allocation in MIMO CR systems aiming at maximizing the spectral efficiency of CR systems [6–9]. In this regards, the work in [10] proposed energy-efficient resource allocation based on IA in CR systems. Nevertheless, this work is focused only on narrow-band CR systems in addition to that it is restricted to a limited number of SUs.

In this work, we investigate energy-efficient resource allocation algorithm based on IA technique in dense MIMO orthogonal frequency division multiplexing (OFDM) CR systems. Resource management problem is formulated on the base of IA in order to enable the SUs to underlay the primary system spectrum. The proposed algorithm satisfies the QoS of the PU by guaranteeing the minimum transmission rate of the PU. In problem formulation, each subcarrier is assigned to a feasible number of SUs in order to meet IA feasibility conditions. The resource allocation problem is formulated as a mixed-integer non-convex optimization problem. To tackle the mixed-integer and non-convexity nature of the problem, a sub-optimal energy-efficient algorithm is proposed through two steps. First step assigns each subcarrier to a feasible number of SUs while the second step allocates the power among all subcarriers and all users.

2 System Model

In this model, K transmitter-receiver pairs are assumed, where a cognitive radio system with $K-1$ pairs of SUs is coexisted with a single-user broadband primary system. All the K nodes are equipped with M_T transmit antennas and M_R receive antennas. User 1 refers to the PU that occupies a bandwidth of B Hertz divided into N subcarriers. Each subcarrier has a bandwidth $W = B/N$ Hertz. Underlay spectrum sharing is assumed through this work, where the SUs guarantee the QoS of the PU. In order to accomplish co-channel interference free transmission, IA is applied to give the opportunity for the different SUs to share the CR spectrum with optimal interference management. Due to the frequency orthogonality of OFDM systems, MIMO IA can be applied independently on each subcarrier as a combination of linear precoder at the transmitter and interference suppression decoder at the receiver [3]. Therefore, we model the system focusing on a specific subcarrier n. For the n^{th} subcarrier, the D symbol data streams $\mathbf{x}_k^n$ are precoded at the k^{th} transmitter using a unitary matrix $\mathbf{V}_k^n \in \mathbb{C}^{M_T \times D}$. This precoder aligns the desired data at its own receiver in the interference-free subspace while the interference signals from other SU transmitters are aligned at the interference subspace [2,11]. With perfect channel knowledge, the received signal at the k^{th} receiver on the n^{th} subcarrier is written as

$$\mathbf{y}_k^n = \mathbf{U}_k^{n\mathrm{H}}\mathbf{H}_{kk}^n\mathbf{V}_k^n\mathbf{x}_k^n + \sum_{j=1, j\neq k}^{K} \mathbf{U}_k^{n\mathrm{H}}\mathbf{H}_{kj}^n\mathbf{V}_j^n\mathbf{x}_j^n + \mathbf{U}_k^{n\mathrm{H}}\mathbf{z}_k^n, \tag{1}$$

where $\mathbf{U}_k^n \in \mathbb{C}^{M_R\times D}$ is a unitary linear interference suppression matrix applied at the k^{th} receiver, and $\mathbf{H}_{kj}^n \in \mathbb{C}^{M_R\times M_T}$ denotes the channel frequency response between j^{th} transmitter and k^{th} receiver. $\mathbf{z}_k^n \in \mathbb{C}^{M_R\times 1}$ is the zero mean unit variance circularly symmetric additive white Gaussian noise (AWGN) vector with variance σ^2 at the k^{th} receiver.

In IA, the interference can be totally nullified when the condition $M_T + M_R - (K+1)D \geq 0$ is achieved [12]. The precoder and decoder matrices can be designed to achieve IA using closed-form solution or other algorithmic methods as presented in the literature for many cases (e.g. [2,13,14] and references therein). In feasible IA systems, the interference is concentrated in the interference subspace, and hence the leakage interference in the desired subspace is trivial [15]. Accordingly, the received signal in (1) becomes

$$\mathbf{y}_k^n = \mathbf{U}_k^{n\mathrm{H}}\mathbf{H}_{kk}^n\mathbf{V}_k^n\mathbf{x}_k^n + \mathbf{U}_k^{n\mathrm{H}}\mathbf{z}_k^n. \tag{2}$$

The total sum-rate of the CR system in addition to the PU is expressed as [13]

$$R = \sum_{n=1}^{N}\sum_{k=1}^{K}\log_2\left|\mathbf{I}_D + \frac{1}{\sigma^2}\mathbf{U}_k^{n\mathrm{H}}\mathbf{H}_{kk}^n\mathbf{V}_k^n\mathbf{S}_k^n\mathbf{U}_k^n\mathbf{H}_{kk}^{n\;\mathrm{H}}\mathbf{V}_k^{n\mathrm{H}}\right|, \tag{3}$$

where $\mathbf{S}_k^n \in \mathbb{R}^{D\times D}$ is the input covariance matrix of the k^{th} user on the n^{th} subcarrier, and hence the transmitted power by the k^{th} user over the n^{th} subcarrier is $P_k^n = \mathrm{Tr}\left(\mathbf{S}_k^n\right)$. Since $\mathbf{U}_k^{n\mathrm{H}}\mathbf{H}_{kk}^n\mathbf{V}_k^n$ is considered as the effective channel and has a rank of D, the sum-rate in (3) can be formulated using spectral decomposition into

$$R = \sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{d=1}^{D}\log_2\left(1 + \frac{P_{k,d}^n\lambda_d\left(\mathbf{U}_k^{n\mathrm{H}}\mathbf{H}_{kk}^n\mathbf{V}_k^n\right)}{\sigma^2}\right), \tag{4}$$

where $P_{k,d}^n$ is the allocated power to the d^{th} data stream at the k^{th} user on the n^{th} subcarrier and $\lambda_d\left(\mathbf{U}_k^{n\mathrm{H}}\mathbf{H}_{kk}^n\mathbf{V}_k^n\right)$ is the d^{th} eigenvalue of $\mathbf{U}_k^{n\mathrm{H}}\mathbf{H}_{kk}^n\mathbf{V}_k^n$. Further, we denote $\lambda_d\left(\mathbf{U}_k^{n\mathrm{H}}\mathbf{H}_{kk}^n\mathbf{V}_k^n\right)$ as $\lambda_{k,d}^n$.

3 Problem Formulation

The energy efficiency is defined as the amount of information being transmitted in one Hertz per Joule energy consumption (bits/Hz/Joule). Our objective is to maximize the energy efficiency of the system while the QoS of the PU is guaranteed. The QoS of the PU is guaranteed as the minimum transmission rate, which is described as

$$\sum_{n=1}^{N}\sum_{d=1}^{D}\log_2\left(1 + \frac{P_{1,d}^n\lambda_{1,d}^n}{\sigma^2}\right) \geq R_Q, \tag{5}$$

where R_Q is the minimum transmission rate that should be guaranteed to achieve the required QoS.

In this work, the overall power consumption is expressed as

$$\mathcal{E} = \sum_{k=1}^{K}\sum_{n=1}^{N}\sum_{d=1}^{D} P_{k,d}^{n} + \sum_{k=1}^{K}\left(P_{ct}^{k} + P_{cr}^{k}\right), \tag{6}$$

where P_{ct}^{k} and P_{cr}^{k} are the transmitter-circuit and the receiver-circuit power consumption for the k^{th} user, respectively [16].

IA allows the SUs to share the spectrum resources simultaneously with the PU, which increases the degrees-of-freedom of the CR system. Nevertheless, according to IA feasibility conditions, the number of SUs that is allowed to share the PU on a given subcarrier is restricted up to a certain number of SUs written as

$$K_f = \frac{M_T + M_R}{D} - 2. \tag{7}$$

Therefore, the formulation of IA based resource management problem should consider this limitation by scheduling only K_f SUs on a given subcarrier. The problem can be formulated as

$$P1 : \arg\max_{\mathcal{P},\mathcal{W}} \frac{R(\mathcal{P},\mathcal{W})}{\mathcal{E}(\mathcal{P},\mathcal{W})} = \frac{\sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{d=1}^{D} w_k^n \log_2\left(1 + \frac{P_{k,d}^{n}\lambda_{k,d}^{n}}{\sigma^2}\right)}{\sum_{k=1}^{K}\sum_{n=1}^{N}\sum_{d=1}^{D}\left(w_k^n P_{k,d}^{n}\right) + \sum_{k=1}^{K}\left(P_{ct}^{k} + P_{cr}^{k}\right)} \tag{8a}$$

$$\text{s.t.} : \sum_{n=1}^{N} w_1^n = N \tag{8b}$$

$$\sum_{n=1}^{N}\sum_{d=1}^{D} w_k^n P_{k,d}^{n} \leq P_k^{\max} \quad \forall k \tag{8c}$$

$$P_{k,d}^{n} \succeq 0, \qquad \forall n, k, d \tag{8d}$$

$$\sum_{n=1}^{N}\sum_{d=1}^{D} \log_2\left(1 + \frac{P_{1,d}^{n}\lambda_{1,d}^{n}}{\sigma^2}\right) \geq R_Q \tag{8e}$$

$$w_k^n \in \{0,1\} \ \forall k, n \tag{8f}$$

$$\sum_{k=2}^{K} w_k^n = K_f \ \forall n, \tag{8g}$$

where $\mathcal{P} = \{P_{k,d}^{n}, \forall k, n, d\}$ and $\mathcal{W} = \{w_k^n = \{0,1\}, \forall k, n\}$ are the power allocation and user selection indicators, respectively. w_k^n is a binary variable that indicates whether the k^{th} SU is allowed to access the n^{th} subcarrier, where $w_k^n = 1$ if and only if the n^{th} subcarrier is allocated to the k^{th} SU and 0 implies otherwise. w_1^n is always 1 since the PU is guaranteed to access all the spectrum which is satisfied by the constraint (8b). The constraint (8c) represents the k^{th} user total power constraint $P_k^{\max}$, while a positive transmission power at each antenna is guaranteed by (8d). The constraint (8e) ensures that the QoS of the

PU as stated in (5). The equality condition $\sum_{k=2}^{K} w_k^n = K_f$ ensures that any given subcarrier can be shared by K_f SUs in addition to the PU, where IA feasibility is accomplished.

4 Sub-optimal Energy-Efficient Algorithm

The optimization problem of $P1$ is a non-convex and mixed-integer optimization problem, which is mostly prohibitive to solve. The non-convexity nature is a result of the objective function which is the ratio of two functions, and the mixed-integer nature comes from the integer constraint that is used for SUs scheduling. Therefore, we propose a sub-optimal scheme in order to solve Problem $P1$ efficiently with low computational complexity. Firstly, we avoid the mixed-integer nature of Problem $P1$ by finding the indicators $\mathcal{W}$ using frequency scheduling. After that, the objective function is simplified using techniques from nonlinear fractional programming in order to allocate the power among users and subcarriers aiming at maximizing the energy efficiency of the system. The detailed description of the sub-optimal algorithm is provided in the next section.

4.1 Frequency Scheduling

The integer constraint, that is used for user scheduling in (8f), is an obstacle in tackling the optimization problem. Therefore, frequency scheduling needs to be performed in case of having a dense CR system, where the number of SUs is greater than K_f, in order to find $\mathcal{W}$. In this step, we schedule K_f SUs to share the PU a given subcarrier. This step can overcome the IA feasibility constraint and guarantees feasible and perfect IA on each subcarrier [17]. The scheduling operation chooses the SUs with strong direct effective channel since this provides more power gain to save extra energy.

The description of the scheduling step can be commenced by defining $\mathcal{N}$ and $\mathcal{B} = \{2, .., K\}$ to be the sets contain all the non-assigned subcarriers and all the SUs, respectively. Furthermore, define $\mathcal{C} = \{c(1), .., c(N_{\mathcal{C}})\}$ to be the sets of all possible combinations of K_f SUs, where $N_{\mathcal{C}}$ denotes the number of combinations while $c(i) \in \mathcal{C}$ refers to the group of users inside the i^{th} combination. The first element in each group is the PU in addition to the K_f SUs. Each combination must satisfy that $c(i) \subseteq \{1, \mathcal{B}\}$ and $c(i) \neq c(j); \forall (i \neq j)$. For the n^{th} subcarrier, the combination selection can be formulated mathematically as

$$c_n^* = \arg\max_{c(i)} \sum_{k \in c(i)} \left\| \mathbf{U}_k^{n\mathrm{H}} \mathbf{H}_{kk}^n \mathbf{V}_k^n \right\|_F, \quad (9)$$

where the SUs inside this cluster are the only allowed to transmit over that subcarrier in addition to the PU.

At the beginning of the scheduling algorithm, all the possible combinations are generated to form $\mathcal{C}$ using the SUs in the set $\mathcal{B}$. Afterwards, the subcarriers are assigned sequentially to groups, where a given subcarrier, e.g the n^{th} subcarrier, is allocated to the combination c_n^* that achieves the scheduling criterion in (9). After finding c_n^*, the indicator w_k^n is set to be 1 for all the SUs in c_n^* and 0 otherwise. The scheme is repeated until allocating all subcarriers among the clusters. The scheduling procedures are included in Algorithm 1.

4.2 Power Allocation

By means of frequency scheduling, the subcarrier indicators $\mathcal{W}$ are already determined. Therefore, the power allocation problem can be formulated as follows

$$P2 : \arg\max_{\mathcal{P}} \frac{R(\mathcal{P})}{\mathcal{E}(\mathcal{P})} = \frac{\sum_{n=1}^{N} \sum_{k \in c_n^*} \sum_{d=1}^{D} \log_2\left(1 + \frac{P_{k,d}^n \lambda_{k,d}^n}{\sigma^2}\right)}{\sum_{n=1}^{N} \sum_{k \in c_n^*} \sum_{d=1}^{D} \left(P_{k,d}^n\right) + \sum_{k=1}^{K} \left(P_{ct}^k + P_{cr}^k\right)} \tag{10a}$$

$$\text{s.t.} : \sum_{n=1}^{N} \sum_{d=1}^{D} P_{k,d}^n \leq P_k^{\max} \quad \forall k \tag{10b}$$

$$P_{k,d}^n \succeq 0, \qquad \forall n, k, d \tag{10c}$$

$$\sum_{n=1}^{N} \sum_{d=1}^{D} \log_2\left(1 + \frac{P_{1,d}^n \lambda_{1,d}^n}{\sigma^2}\right) \geq R_Q. \tag{10d}$$

Hence, the optimization problem $P2$ is now non-convex quasiconcave fractional program, where the numerator is concave in $P_{k,d}^n$ and the denominator is affine [18]. Since quasiconcave fractional programs share some important properties with concave programs [19], it is possible to solve concave-convex fractional programs with many of the standard methods for concave programs.

In this work, the iterative Dinkelbach's method [20] is deployed to solve the quasiconcave problem of $P2$ in a parameterized concave form. Let χ is a compact set of feasible solutions of the optimization problem, where $\mathcal{P} \in \chi$. The following objective function

$$\arg\max_{\mathcal{P} \in \chi} \frac{R(\mathcal{P})}{\mathcal{E}(\mathcal{P})}$$

can be associated using Dinkelbach's method [20] with the following parametric concave program

$$\mathcal{F}(\lambda) = \arg\max_{\mathcal{P} \in \chi} R(\mathcal{P}) - \lambda \mathcal{E}(\mathcal{P}), \tag{11}$$

where $\lambda \in \mathbb{R}$ is treated as a parameter. It can be shown that $\mathcal{F}(\lambda)$ is convex, continuous and strictly decreasing in λ [20]. We define λ^* as the maximum energy efficiency of the considered system which is given by

$$\lambda^* = \frac{R(\mathcal{P}^*)}{\mathcal{E}(\mathcal{P}^*)} = \arg\max_{\mathcal{P} \in \chi} \frac{R(\mathcal{P})}{\mathcal{E}(\mathcal{P})}. \tag{12}$$

According to Dinkelbach's method [20], we can achieve the maximum energy efficiency λ^* when

$$\arg\max_{\mathcal{P}\in\chi} R(\mathcal{P}) - \lambda^*\mathcal{E}(\mathcal{P}) = R(\mathcal{P}^*) - \lambda^*\mathcal{E}(\mathcal{P}^*) = 0 \tag{13}$$

for $R(\mathcal{P}) \geq 0$ and $\mathcal{E}(\mathcal{P}) > 0$ [20,21].

In summary, Dinkelbach proposes an iterative method to find increasing values of feasible λ by solving the parameterized problem

$$\mathcal{F}(\lambda_l) = \arg\max_{\mathcal{P}\in\chi} R(\mathcal{P}) - \lambda_l\mathcal{E}(\mathcal{P}), \tag{14}$$

where λ_l denotes the l^{th} iteration. The iterative process continues until the absolute difference value $|\mathcal{F}(\lambda_l)|$ becomes as small as a pre-specified ϵ.

Accordingly, Problem $P2$ is turned into solving a group of convex problems, which is definitely more manageable. Therefore, for a given λ, Problem $P2$ becomes

$$P3 : \arg\max_{\mathcal{P}} \left(\sum_{n=1}^{N}\sum_{k\in c_n^*}\sum_{d=1}^{D}\log_2\left(1+\frac{P_{k,d}^n\lambda_{k,d}^n}{\sigma^2}\right)\right) - \tag{15a}$$

$$\lambda \times \left(\sum_{n=1}^{N}\sum_{k\in c_n^*}\sum_{d=1}^{D}P_{k,d}^n + \sum_{k=1}^{K}\left(P_{ct}^k + P_{cr}^k\right)\right)$$

$$\text{s.t.} : \sum_{n=1}^{N}\sum_{d=1}^{D}P_{k,d}^n \leq P_k^{\max} \quad \forall k \tag{15b}$$

$$P_{k,d}^n \succeq 0, \qquad \forall n,k,d \tag{15c}$$

$$\sum_{n=1}^{N}\sum_{d=1}^{D}\log_2\left(1+\frac{P_{1,d}^n\lambda_{1,d}^n}{\sigma^2}\right) \geq R_Q. \tag{15d}$$

Problem $P3$ is convex, where the Lagrangian can be written as

$$\mathcal{L} = \sum_{n=1}^{N}\sum_{k\in c_n^*}\sum_{d=1}^{D}\log_2\left(1+\frac{P_{k,d}^n\lambda_{k,d}^n}{\sigma^2}\right) - \lambda\times\left(\sum_{n=1}^{N}\sum_{k\in c_n^*}\sum_{d=1}^{D}P_{k,d}^n + \sum_{k=1}^{K}\left(P_{ct}^k + P_{cr}^k\right)\right) \tag{16}$$

$$+\alpha\left(\sum_{n=1}^{N}\sum_{d=1}^{D}\log_2\left(1+\frac{P_{1,d}^n\lambda_{1,d}^n}{\sigma^2}\right) - R_Q\right)$$

$$+\sum_{k=1}^{K}\sum_{n=1}^{N}\sum_{d=1}^{D}P_{k,d}^n\mu_{k,d}^n - \sum_{k=1}^{K}\beta_k\left(\sum_{n=1}^{N}\sum_{d=1}^{D}P_{k,d}^n - P_k^{\max}\right),$$

where α is the non-negative Lagrange multiplier corresponding to the minimum PU QoS rate in (15d). The Lagrange multiplier vector $\boldsymbol{\mu}$, which has non-negative elements $\mu_{k,d}^n \forall n,k,d$, considers the positive power transmission in (15c). $\boldsymbol{\beta}$ is the Lagrange multiplier vector corresponding to the maximum power budget for each user in the system as in (15b), which has non-negative elements $\beta_k, \forall k$. After rearranging the Karush-Kuhn-Tucker (KKT) conditions, we get

$$P_{1,d}^n = \left[\frac{1+\alpha}{\lambda + \sum_{k=1}^{K} \beta_k} - \frac{\sigma^2}{\lambda_{k,d}^n} \right]^+ \tag{17}$$

$$P_{k,d}^n = \left[\frac{1}{\lambda + \sum_{k=1}^{K} \beta_k} - \frac{\sigma^2}{\lambda_{k,d}^n} \right]^+ , \tag{18}$$

where $[y]^+ = \max(0, y)$. These Lagrange multipliers can be solved numerically using ellipsoid or interior point method.

Remark: At low SNR, Problem $P3$ may have no solution since the constraint in (15d) is not feasible to be achieved. To avoid this case, we firstly check if the constraint in (15d) is feasible or not [10]. This can be satisfied by switching the SUs into sleep mode and performing power allocation aiming at maximizing the throughput of the PU as follow

$$P4: \max_{P_{1,d}^n} \sum_{n=1}^{N} \sum_{d=1}^{D} \log_2 \left(1 + \frac{P_{1,d}^n \lambda_{1,d}^n}{\sigma^2}\right) \tag{19a}$$

$$\text{s.t.}: \sum_{n=1}^{N} \sum_{d=1}^{D} P_{1,d}^n \leq P_1 \tag{19b}$$

$$P_{1,d}^n \geq 0. \tag{19c}$$

This problem can be efficiently solved using a successive application of the conventional waterfilling concept as follows [22]

$$\hat{P}_{1,d}^n = \left[\nu - \frac{\sigma^2}{\lambda_{1,d}^n} \right]^+ , \tag{20}$$

where ν is the waterfilling level. The constraint in (15d) is feasible if and only if $\sum_{n=1}^{N} \sum_{d=1}^{D} \log_2 \left(1 + \frac{\hat{P}_{1,d}^n \lambda_{1,d}^n}{\sigma^2}\right) \geq R_Q$. Otherwise, the transmission mode is changed from IA into single user PU MIMO system as in [10] in order to provide the PU with the full resources to achieve the maximum throughout.

4.3 The Proposed Algorithm

The proposed energy-efficient IA algorithm for MIMO-OFDM CR systems is summarized in Algorithm 1. As discussed before, frequency scheduling is performed in order to obtain $\mathcal{W}^*$ as in the steps 1-14. After that, we check whether

Algorithm 1. Sub-Optimal Energy-Efficient Algorithm

1: Initialize $\mathcal{N} = \{1, 2, .., N\}$, $\mathcal{B} = \{2, .., K\}$, the maximum number of iterations L and the maximum tolerance ϵ
2: Set $\lambda = 0$ and iteration index $l = 0$
3: Find $\mathcal{C}$
4: $n = \mathcal{N}(1)$; (the first element in $\mathcal{A}$)
5: **while** $\mathcal{N}$ is not empty **do**
6:     **for all** $c(i) \in \mathcal{C}$ **do**
7:         Find $\mathbf{V}_k^n$ and $\mathbf{U}_k^n$; $\forall k \in c(i)$
8:         Evaluate $\psi^n = \sum_{k \in c(i)} \left\| \mathbf{U}_k^{n\mathrm{H}} \mathbf{H}_{kk}^n \mathbf{V}_k^n \right\|_F$
9:     **end for**
10:     Choose the set c_n^* such that ψ^n is maximized
11:     Set $w_k^n = 1 \; \forall k \in c_n^*$ and 0 otherwise
12:     Remove n from $\mathcal{N}$ and Set $n = n + 1$
13: **end while**
14: **Output** $\mathcal{W}^*$
15: Switch SUs into sleep mode and solve Problem $P4$ using (20)
16: **if** $\sum_{n=1}^{N} \sum_{d=1}^{D} \log_2 \left(1 + \frac{\hat{P}_{1,d}^n \lambda_{1,d}^n}{\sigma^2} \right) \geq R_Q$ **then**
17:     Switch on SUs
18:     **while Convergence** = False and $l < L$ **do**
19:         Solve Problem $P3$ as in (17) and (18) and obtain $\acute{\mathcal{P}}$
20:         **if** $R(\acute{\mathcal{P}}) - \lambda_l \mathcal{E}(\acute{\mathcal{P}}) < \epsilon$ **then**
21:             **Convergence** = True
22:             **Return** $\mathcal{P}^* = \acute{\mathcal{P}}$ and $\lambda^* = \frac{R(\mathcal{P}^*)}{\mathcal{E}(\mathcal{P}^*)}$
23:         **else if** ; **then**
24:             Set $l = l + 1$ and $\lambda_l = \frac{R(\acute{\mathcal{P}})}{\mathcal{E}(\acute{\mathcal{P}})}$
25:             **Convergence** = False
26:         **end if**
27:     **end while**
28: **else if** ; **then**
29:     Change transmission mode of the PU into single user MIMO and Switch SUs into sleep mode.
30: **end if**

the available resources are sufficient to guarantee the minimum QoS rate. When QoS is guaranteed, the power is allocated by solving a group of convex problems aiming at finding $\mathcal{P}^*$ as in the steps 17-26. Otherwise, the PU utilizes the full resources in order to maximize the throughput of the primary system by changing the transmission mode into single user MIMO system.

5 Simulation Results

In this section, we evaluate the performance of the proposed energy-efficient resource allocation algorithm using numerical simulations. A PU that occupies 5 MHz bandwidth is assumed, where the number of subcarriers is $N = 64$. Each

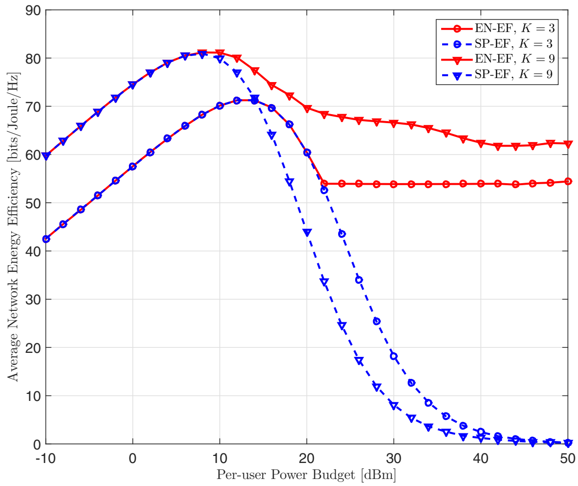

Fig. 1. Network energy efficiency versus maximum per-user power budget $P_k^{\max}$ for different numbers of users.

subcarrier has a bandwidth of 78.128 kHz, and the noise variance is $\sigma^2 = -60$ dBm. A CR system is assumed to share the PU spectrum based on IA technique. For all nodes in this scenario, the PU and SUs, are equipped with 2 antennas $M_T = M_R = 2$, and each node sends one data stream. Channel realizations have been drawn from independent and identically distributed Gaussian distribution with zero mean and unit variance. The circuit power consumption of the transmit circuit and receive circuit is assumed to be $P_{ct}^k = P_{cr}^k = 32$ dBm for all users. The minimum data-rate requirement for the PU is $R_Q = 25$ Mbits/s. For the purpose of performance comparison, the following algorithms are considered in the simulation:

1. **EN-EF**: Resource management is performed according to the proposed energy-efficient method as described in Algorithm 1.
2. **SP-EF**: The resources are allocated aiming at maximizing the spectral effeceincy as described in [9].

Fig. 1 depicts the average system energy efficiency versus the maximum per-user transmit power budget $P_k^{\max}$. At low SNR regime, it can be observed that the energy efficiency of *EN-EF* algorithm increases as the maximum per-user transmit power budget increases until reaching the maximum energy efficiency. After that, this scheme slightly decreases and converges to a specific energy efficiency value, where any additional increase in the transmitted power is not beneficial from energy efficiency point of view. It is noted for *EN-EF* algorithm that as the number of users increases the energy efficiency performance gets more benefit from the multiuser diversity, which is translated to commence an additional power gain to the system and save energy. On the other side, the energy efficiency of *SP-EF* algorithm behaves identical to *EN-EF* at low SNR

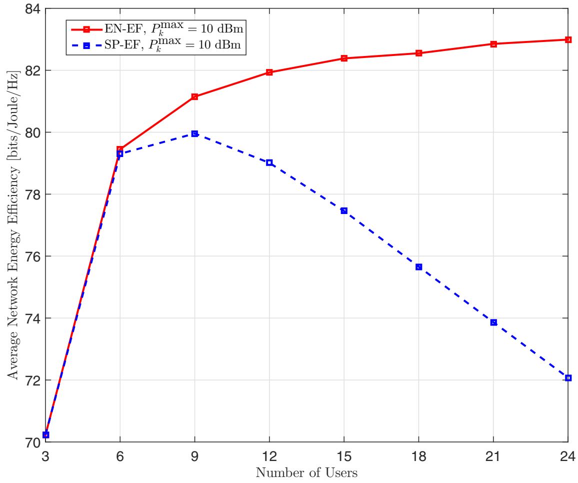

Fig. 2. Network energy efficiency versus the number of users when per-user power budget $P_k^{\max} = 10$ dBm.

regime while its energy efficiency performance dramatically decreases with the increase of the maximum per-user transmit power budget since each user uses the maximum power budget to maximize the sum-rate of the system. It is noted that the energy efficiency of *SP-EF* scheme at middle and high SNR regimes decreases as the number of SUs increases since each user uses its power budget and, hence, as the number of SUs increases the used power increases. This result is more clarified in Fig. 2 where this figure presents the energy efficiency of both schemes with the number of users when per-user power budget $P_k^{\max} = 10$ dBm. It is noted that the energy efficiency of *EN-EF* scheme increases with the number of users while *SP-EF* scheme decreases.

6 Conclusion

In this paper, we propose an energy-efficient resource allocation algorithm for MIMO-OFDM CR systems that underly a PU. The optimization problem is formulated as a non-convex mixed-integer problem, in which the per-user power budget and the QoS of the PU are considered. The problem is handled through two steps. In the first step, frequency scheduling is performed to allocate the subcarriers among the SUs. In the second step, the power allocation is considered by exploiting Dinkelbach's method, where an iterative power allocation algorithm is proposed for maximizing the system energy efficiency. Simulations show that the proposed scheme provides considerable gains on energy efficiency with ensuring the QoS of the PU.

References

1. Haykin, S.: Cognitive radio: brain-empowered wireless communications. IEEE Journal on Selected Areas in Communications 201–220 (February 2005)
2. Cadambe, V.R., Jafar, S.: Interference alignment and degrees of freedom of the K-user interference channel. IEEE Transactions on Information Theory 3425–3441 (2008)
3. Cadambe, V.R., Jafar, S.: Reflections on interference alignment and the degrees of freedom of the K-user MIMO interference channel. IEEE Information Theory Society Newsletter 5–8 (2009)
4. Feng, D., Jiang, C., Lim, G., Cimini, L.J., Feng, G., Li, G.Y.: A survey of energy-efficient wireless communications. IEEE Communications Surveys Tutorials **15**(1), 167–178 (2013)
5. Han, C., Harrold, T., Armour, S., Krikidis, I., Videv, S., Grant, P., Haas, H., Thompson, J.S., Ku, I., Wang, C., Le, T.A., Nakhai, M.R., Zhang, J., Hanzo, L.: Green radio: radio techniques to enable energy-efficient wireless networks. IEEE Communications Magazine **49**(6), 46–54 (2011)
6. Perlaza, S.M., Fawaz, N., Lasaulce, S., Debbah, M.: From spectrum pooling to space pooling: Opportunistic interference alignment in MIMO cognitive networks. IEEE Transactions on Signal Processing **58**(7), 3728–3741 (2010)
7. Sboui, L., Ghazzai, H., Rezki, Z., Alouini, M.-S.: Achievable rate of cognitive radio spectrum sharing MIMO channel with space alignment and interference temperature precoding. In: IEEE International Conference on Communications (ICC), pp. 2656–2660 (2013)
8. El-Absi, M., Shaat, M., Bader, F., Kaiser, T.: Interference alignment based resource management in MIMO cognitive radio systems. In: Proceedings of 20th European Wireless Conference, pp. 1–6, May 2014
9. El-Absi, M., Shaat, M., Bader, F., Kaiser, T.: Interference alignment with frequency-clustering for efficient resource allocation in cognitive radio networks. In: IEEE Global Communications Conf. (Globecom), December 8–12, 2014
10. Zhao, N., Yu, F.R., Sun, H.: Power allocation for interference alignment based cognitive radio networks. In: 2014 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), pp. 742–746, April 2014
11. Jafar, S., Fakhereddin, M.J.: Degrees of freedom for the MIMO interference channel. IEEE Transactions on Information Theory **53**(7), 2637–2642 (2007)
12. Yetis, C., Gou, T., Jafar, S., Kayran, A.: On feasibility of interference alignment in MIMO interference networks. IEEE Transactions on Signal Processing **58**, 4771–4782 (2010)
13. Gomadam, K., Cadambe, V.R., Jafar, S.: A distributed numerical approach to interference alignment and applications to wireless interference networks. IEEE Transactions on Information Theory **57**(6), 3309–3322 (2011)
14. El-Absi, M., El-Hadidy, M., Kaiser, T.: A distributed interference alignment algorithm using min-maxing strategy. Transactions on Emerging Telecommunications Technologies (2014)
15. Zhao, N., Yu, F.R., Sun, H.: Adaptive energy-efficient power allocation in green interference alignment wireless networks. IEEE Transactions on Vehicular Technology **PP**(99), 1 (2014)
16. Cui, S., Goldsmith, A., Bahai, A.: Energy-constrained modulation optimization. IEEE Transactions on Wireless Communications **4**(5), 2349–2360 (2005)

17. Zhao, N., Qu, T., Sun, H., Nallanathan, A., Yin, H.: Frequency scheduling based interference alignment for cognitive radio networks. In: 2013 IEEE Global Communications Conference (GLOBECOM), pp. 3447–3451, December 2013
18. Boyd, S., Vandenberghe, L.: Convex Optimization. Cambridge University Press, New York (2004)
19. Schaible, S.: Fractional programming. In: Handbook of global optimization, vol. 2 of Nonconvex Optim. Appl. Kluwer Acad. Publ., Dordrecht, pp. 495–608 (1995)
20. Schaible, S.: Fractional programming. ii, on Dinkelbach's algorithm. Management Science **22**(8), 868–873 (1976)
21. Isheden, C., Chong, Z., Jorswieck, E., Fettweis, G.: Framework for link-level energy efficiency optimization with informed transmitter. IEEE Transactions on Wireless Communications **11**(8), 2946–2957 (2012)
22. Tse, D., Viswanath, P.: Fundamentals of Wireless Communication. Cambridge University Press, Wiley series in telecommunications (2005)