Spectral Efficient Optimization in OFDM Systems with Wireless Information and Power Transfer

Derrick Wing Kwan Ng* and Robert Schober*

*Institute for Digital Communications, Universität Erlangen-Nürnberg, Germany

Abstract—This paper considers an orthogonal frequency division multiplexing (OFDM) point-to-point wireless communication system with simultaneous wireless information and power transfer. We study a receiver which is able to harvest energy from the desired signal, noise, and interference. In particular, we consider a power splitting receiver which dynamically splits the received power into two power streams for information decoding and energy harvesting. We design power allocation algorithms maximizing the spectral efficiency (bit/s/Hz) of data transmission. In particular, the algorithm design is formulated as a nonconvex optimization problem which takes into account the constraint on the minimum power delivered to the receiver. The problem is solved by using convex optimization techniques and a one-dimensional search. The optimal power allocation algorithm serves as a system benchmark scheme due to its high complexity. To strike a balance between system performance and computational complexity, we also propose two suboptimal algorithms which require a low computational complexity. Simulation results demonstrate the excellent performance of the proposed suboptimal algorithms.

I. INTRODUCTION

Orthogonal frequency division multiplexing (OFDM) is a promising air interface to fulfill the growing demands for a high spectral efficiency, due to its flexibility in resource allocation and high resistance against channel delay spread. Nevertheless, in energy limited wireless networks, the lifetime of communication nodes remains the bottleneck in guaranteeing quality of service (QoS) due to the constrained energy supply. Recently, energy harvesting technology has received considerable interest from both industry and academia. In particular, it has become a viable solution for prolonging the lifetime of networks since it provides a perpetual energy source and self-sustainability to systems [1]-[6].

Traditionally, tides, solar, and wind are the major natural renewable energy sources for energy harvesting. Unfortunately, the availability of these energy sources is limited by climate or location which may be problematic in indoor environments. On the other hand, harvesting energy from ambient radio signals in radio frequency (RF) introduces a new paradigm of energy management. More importantly, wireless energy harvesting provides the possibility for simultaneous wireless information and power transfer [3]-[6]. Nevertheless, this combination poses many new challenges for the design of resource allocation algorithms and receivers. In [3] and [4], the optimal tradeoff between power and information transfer was studied for different system settings. However, the receivers in [3] and [4] are assumed to be able to decode information and extract power from the same received signal, which cannot be achieved in practice yet. Consequently, a power splitting receiver was proposed in [5] and [6] for facilitating simultaneous information decoding and energy harvesting. In particular, the authors in [6] studied the resource allocation algorithm design for power splitting

receivers of single carrier systems in ergodic fading channels. Yet, the assumption of channel ergodicity may not be justified in slow fading channels and the results in [6] may not be applicable to multicarrier systems. Besides, an algorithm for maximizing the spectral efficiency of a system with power splitting receiver has not been reported in the literature so far.

Motivated by the aforementioned prior works, in this paper, we first derive an optimal algorithm for maximizing the system spectral efficiency in slow fading channels. Due to the associated high computational complexity of the optimal algorithm, we propose two suboptimal resource allocation algorithms with low computational complexity which are based on the coordinate ascent method and convex optimization techniques.

II. SYSTEM MODEL

In this section, we present the adopted system model.

A. OFDM Channel Model

A point-to-point OFDM system consisting of one transmitter and one receiver is considered. We assume that the receiver is able to decode information and harvest energy from noise and radio signals (desired signal and interference signal). All transceivers are equipped with a single antenna, cf. Figure 1. There are n_F subcarriers sharing the system bandwidth of $\mathcal{B}$ Hertz; each subcarrier has a bandwidth of $W = \mathcal{B}/n_F$ Hertz. The channel impulse response is assumed to be time invariant (slow fading) and the channel gain is available at the transmitter for resource allocation purpose. In addition, the receiver is impaired by a co-channel interference signal emitted by an unintended transmitter. The downlink received symbol at the receiver on subcarrier $i \in \{1, \ldots, n_F\}$ is given by

$$Y_i = \sqrt{P_i g l} H_i X_i + I_i + Z_i^s + Z_i^a, \tag{1}$$

where X_i, P_i, and H_i are the transmitted symbol, the transmitted power, and the multipath fading coefficient on subcarrier i, respectively. l and g denote the path loss attenuation and shadowing between the transmitter and receiver, respectively. Z_i^s is the signal processing noise on subcarrier i with zero mean and variance $\sigma_{z^s}^2$. Z_i^s is caused by quantization errors. Z_i^a is the antenna noise on subcarrier i which is modeled as additive white Gaussian noise (AWGN) with zero mean and variance $\sigma_{z^a}^2$. I_i is the received interference signal on subcarrier i with zero mean and variance $\sigma_{I_i}^2$.

B. Hybrid Energy Harvesting and Information Receiver

In practice, the signal used for information decoding cannot be reused for harvesting energy due to hardware limitations [6]. As a result, we follow a similar approach as in [6] and focus on a power splitting receiver to facilitate the concurrent information decoding and energy harvesting. In particular, the receiver splits the received signal into two power streams carrying proportions of ρ_i and $1 - \rho_i$ of the total received signal power before any active analog/digial signal processing is
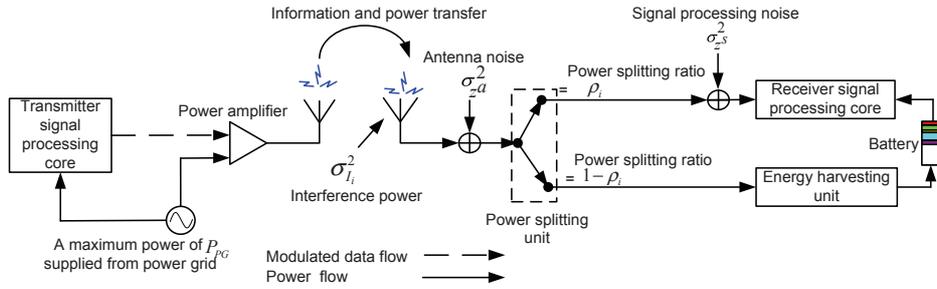
Fig. 1. Communication system model for simultaneous wireless information and power transfer.

performed, cf. Figure 1. Consequently, the two streams carrying a fraction of ρ_i and $1 - \rho_i$ of the total received signal power are used for decoding the information embedded in the signal and energy harvesting, respectively[1].

III. RESOURCE ALLOCATION

In this section, we first introduce the system capacity and then formulate the corresponding resource allocation algorithm design as optimization problem.

A. Instantaneous Channel Capacity

The channel capacity (maximum spectral efficiency) between the transmitter and the receiver on subcarrier i with channel bandwidth W is given by

$$C_i = W \log_2 \left(1 + P_i \Gamma_i\right) \quad \text{with} \tag{2}$$

$$\Gamma_i = \frac{\rho_i l g |H_i|^2}{\rho_i (\sigma_{z^a}^2 + \sigma_{I_i}^2) + \sigma_{z^s}^2}, \tag{3}$$

where $P_i \Gamma_i$ is the received signal-to-interference-plus-noise ratio (SINR) on subcarrier i. Here, the interference and signal processing noise are treated as AWGN for simplifying the algorithm design. The *system capacity* is defined as the aggregate number of bits delivered to the receiver over n_F subcarriers and is given by

$$U(\mathcal{P}, \boldsymbol{\rho}) = \sum_{i=1}^{n_F} C_i, \tag{4}$$

where $\mathcal{P} = \{P_i \geq 0, \forall i\}$ is the power allocation policy and $\boldsymbol{\rho} = \{0 \leq \rho_i \leq 1, \forall i\}$ is the power splitting ratio policy.

B. Optimization Problem Formulation

The optimal resource allocation policy, $\{\mathcal{P}^*, \boldsymbol{\rho}^*\}$, can be obtained by solving the following optimization problem:

$$\max_{\mathcal{P}, \rho} U(\mathcal{P}, \boldsymbol{\rho})$$

$$\text{s.t. } C1: \sum_{i=1}^{n_F} P_i |H_i|^2 g l \eta (1 - \rho_i) \geq P_{\min}^{req},$$

$$C2: \sum_{i=1}^{n_F} P_i \leq P_{\max}, \quad C3: P_C + \sum_{i=1}^{n_F} \varepsilon P_i \leq P_{PG},$$

$$C4: \rho_i = \rho_j, \forall j \neq i, \quad C5: P_i \geq 0, \ \forall i,$$

$$C6: 0 \leq \rho_i \leq 1, \forall i. \tag{5}$$

Here, $P_{\min}^{req}$ in C1 is the minimum required power transfer to the receiver which represents a QoS requirement. η denotes

the energy harvesting efficiency of the receiver in converting the received radio signal to electrical energy for storage. C2 constrains the maximum transmit power of the transmitter such that it will not exceed $P_{\max}$. In practice, the value of $P_{\max}$ is related to hardware limitations of the transmitter and/or the maximum spectrum mask specified by regulations. Variables P_C and ε in C3 are two constants account for the circuit power consumption in the transmitter and the inefficiency of the power amplifier, respectively. C3 indicates that the maximum power supply from the power grid is P_{PG}, cf. Figure 1, and the total power consumption of the transmitter is controlled to be less than P_{PG}. C4 accounts for the hardware limitations of the power splitting receiver. In particular, ρ_i is required to be identical for all subcarriers. Otherwise, an analog adaptive passive frequency selective power splitter is required at the receiver which results in a high system complexity.

IV. SOLUTION OF THE OPTIMIZATION PROBLEM

Problem (5) belongs to the class of nonconvex optimization problems. In particular, the power splitting ratio, ρ_i, couples with the power allocation variable, P_i, in the SINR on each subcarrier which makes (2) a nonconvex function with respect to (w.r.t.) ρ_i and P_i. As a result, efficient convex optimization techniques may not be applicable for obtaining the global optimal solution. In the following, we propose an optimal algorithm and two suboptimal algorithms for system capacity maximization. The optimal resource allocation algorithm comprises a full search for ρ_i and convex optimization techniques. Specifically, we maximize the system capacity w.r.t. the transmit power for a given fixed ρ_i. Then, we repeat the procedure for all possible values of ρ_i and record the corresponding achieved system capacities[2]. At the end, we select that ρ_i as the optimal power splitting ratio from all the trials which provides the maximum system capacity. We note that although the optimal resource allocation algorithm achieves the global optimal system performance, it incurs a prohibitively high computational complexity to the transmitter which is not desirable for time constrained wireless communication services.

A. Optimal Algorithm

In this subsection, we solve the power allocation optimization problem by convex optimization techniques for a given set of $\boldsymbol{\rho}$. To this end, we first obtain the Lagrangian function of (5):

$$\mathcal{L}(\lambda, \beta, \gamma, \mathcal{P}) \tag{6}$$

$$= \sum_{i=1}^{n_F} C_i - \lambda \left(P_C + \sum_{i=1}^{n_F} \varepsilon P_i - P_{PG}\right)$$

$$- \beta \left(\sum_{i=1}^{n_F} P_i - P_{\max}\right) - \gamma \left(P_{\min}^{req} - \sum_{i=1}^{n_F} P_i |H_i|^2 g l \eta (1 - \rho_i)\right).$$

---

[1]For the sake of presentation, we assume that the power splitting ratio can be different across different subcarriers at the moment. The implementation constraints on the power splitting will be taken into account when we introduce the problem formulation for resource allocation algorithm design.

[2]In general, an n_F dimensions full search is required to obtain the optimal power splitting ratio. Yet, the search space can be reduced to a one-dimensional search because of constraint C4.

TABLE I
ITERATIVE RESOURCE ALLOCATION ALGORITHM.

Algorithm Suboptimal Resource Allocation 1
1: Initialization: $N_{\max}$ = the maximum number of iterations and Δ = the maximum tolerance
2: Set iteration index $n = 0$ and initial resource allocation policy $\{\mathcal{P}_n, \boldsymbol{\rho}_n\}$
3: **repeat** {Iteration}
4: For a given set of $\boldsymbol{\rho}_n$, obtain an intermediate power allocation $\mathcal{P}'_n$ from (7)
5: For a given set of $\mathcal{P}'_n$, obtain an intermediate power splitting ratio $\boldsymbol{\rho}'_n$ from (8)
6: **if** $\|U(\mathcal{P}'_n, \boldsymbol{\rho}'_n) - U(\mathcal{P}_n, \boldsymbol{\rho}_n)\| < \Delta$ **then**
7:   Convergence = **true**
8:   **return** $\{\mathcal{P}^*, \boldsymbol{\rho}^*\} = \{\mathcal{P}', \boldsymbol{\rho}'_n\}$
9: **else**
10:   Set $\{\mathcal{P}_n, \boldsymbol{\rho}_n\} = \{\mathcal{P}'_n, \boldsymbol{\rho}'_n\}$ and $n = n + 1$
11:   Convergence = **false**
12: **end if**
13: **until** Convergence = **true** or $n = N_{\max}$

Here, $\gamma, \beta, \lambda \geq 0$ are the Lagrange multipliers associated with the transmitter power usage constraints C1, C2, and C3, respectively. The non-negative transmit power constraint in C5 will be captured in the Karush-Kuhn-Tucker (KKT) conditions[3] when we derive the optimal transmit power. We note that constraints C4 and C6 do not contribute to the Lagrangian function since they are independent of P_i. Yet, these constraints will be considered in the full search over ρ_i.

Then, by using the KKT conditions for a fixed set of Lagrange multipliers, the optimal power allocation on subcarrier i is obtained as

$$P_i^* = \left[\frac{W}{\ln(2)(\alpha + \beta - \gamma)} - \frac{\rho_i(\sigma_{z^a}^2 + \sigma_{I_i}^2) + \sigma_{z^s}^2}{\rho_i lg|H_i|^2} \right]^+, \forall i, \quad (7)$$

and $[x]^+ = \max\{0, x\}$. It can be observed from (7) that the power allocation solution is in the form of water-filling. Since ρ_i is fixed in this optimization framework, the influence of ρ_i is treated as part of the channel gain. Lagrange multiplier γ forces the transmitter to allocate more power for transmission to fulfill the minimum power transfer requirement $P_{\min}^{req}$. The optimal Lagrange multipliers can be easily found via the gradient method or off-the-shelf numerical solvers [7], [8].

In the following, we focus on the design of two suboptimal power allocation algorithms with low computational complexity compared to the optimal power allocation algorithm.

B. Suboptimal Algorithm 1

The problem formulation in (5) is concave w.r.t. $\mathcal{P}$ or $\boldsymbol{\rho}$, but not jointly concave w.r.t. both of them. As a result, an iterative coordinate ascent method is proposed to obtain a locally optimal solution [7] of (5) and the algorithm is summarized in Table I. $\mathcal{P}_n$ and $\boldsymbol{\rho}_n$ denote the power allocation and power splitting policy in the nth iteration, respectively. The overall algorithm is implemented by a loop which solves two optimization problems iteratively. In each iteration, we execute line 4 in Table I by first keeping the power splitting ratio $\boldsymbol{\rho}_n$ fixed and optimizing $\mathcal{P}_n$ via (7). Then in line 5, we keep the updated transmit power $\mathcal{P}_n$ fixed and optimize $\boldsymbol{\rho}_n$. The procedure iterates between line 4 and

---

[3]Since the problem is concave w.r.t. $\mathcal{P}$ for a given set of $\boldsymbol{\rho}$ and it satisfies Slater's constraint qualification, the KKT conditions provide necessary and sufficient conditions for the optimal transmit power allocation.

line 5 until the algorithm converges or the maximum number of iterations has been reached. We note that the convergence to a local optimal solution is guaranteed [7].

For solving the power splitting ratio $\boldsymbol{\rho}_n$ with a fixed $\mathcal{P}_n$ in line 5, we apply the KKT conditions for (5) which yields

$$\rho_i^* = \left[\frac{\Theta_i/2/(\sigma_{z^a}^2 + \sigma_{I_i}^2)/(\gamma + \sum_{j \neq i}\sum_i \zeta_{i,j})}{\sqrt{\ln(2)}\left((\sigma_{z^a}^2 + \sigma_{I_i}^2) + |H_i|^2 lg P_i\right)} \right.$$
$$\left. - \frac{(\sigma_{z^a}^2 + \sigma_{I_i}^2)\,\sigma_{z^s}^2 + \frac{|H_i|^2 lg P_i \sigma_{z^s}^2}{2}}{(\sigma_{z^a}^2 + \sigma_{I_i}^2)\left((\sigma_{z^a}^2 + \sigma_{I_i}^2) + |H_i|^2 lg P_i\right)} \right]_0^1 \quad (8)$$

where $\Theta_i = \sqrt{|H_i|^2 lg P_i \sigma_{z^s}^2 (\gamma + \sum_{j \neq i}\sum_i \zeta_{i,j})\Phi_i}$, $\Phi_i = 4W(\sigma_{z^a}^2 + \sigma_{I_i}^2)^2 + 4W|H_i|^2 lg P_i(\sigma_{z^a}^2 + \sigma_{I_i}^2) + |H_i|^2 lg P_i \sigma_{z^s}^2 (\gamma + \sum_{j \neq i}\sum_i \zeta_{i,j})\ln(2)$, and $\zeta_{i,j}$ is a two-dimensional Lagrange multiplier chosen to satisfy the consensus constraint C4. Operator $[x]_d^c$ is defined as $[x]_d^c = c$, if $x > c$, $[x]_d^c = x$, if $d \leq x \leq c$, $[x]_d^c = d$, if $d > x$, respectively. It can be verified that ρ_i^* is a monotonic increasing function of P_i, i.e., $\frac{\partial \rho_i^*}{\partial P_i} > 0$. As a result, we expect that when P_i is large enough, ρ_i^* will have a value close to 1. We note that the proposed suboptimal algorithm has a polynomial time complexity due to the convexity of the problem formulation w.r.t. the individual optimization variables.

C. Suboptimal Algorithm 2

In this section, we propose a suboptimal resource allocation algorithm which is asymptotically optimal in the high SINR regime. For facilitating the design of an efficient resource allocation algorithm, we augment the optimization variable space by replacing ρ_i with two auxiliary variables, i.e., ρ_i^I and ρ_i^E. Specifically, ρ_i^I and ρ_i^E are associated with the power splitting ratios of the power streams for information decoding and energy harvesting, respectively. Note that $\rho_i^I + \rho_i^E = 1$ has to be satisfied which indicates that the power splitting unit does not introduce any extra power gain to the received signal. In addition, we rewrite and approximate the channel capacity between the transmitter and the receiver on subcarrier i as

$$C_i = W \log_2\left(1 + \frac{P_i \rho_i^I lg|H_i|^2}{\rho_i^I(\sigma_{z^a}^2 + \sigma_{I_i}^2) + \sigma_{z^s}^2}\right) \quad (9)$$
$$\approx W \log_2\left(\frac{P_i \rho_i^I lg|H_i|^2}{\rho_i^I(\sigma_{z^a}^2 + \sigma_{I_i}^2) + \sigma_{z^s}^2}\right)$$

in high SINR, i.e., $\log_2(1 + x) \approx \log_2(x), x \gg 1$. As a result, the objective function is now jointly concave w.r.t. ρ_i^I and P_i since the two eigenvalues of the Hessian matrix of C_i, $\frac{-1}{P_i^2 \log(2)}$ and $-\frac{(\sigma_{z^s}^2)^2 + \rho_i^I\left(2\,\sigma_{z^a}^2 + 2\,\sigma_{I_i}^2\right)\sigma_{z^s}^2}{(\rho_i^I)^2 \log(2)\left(\sigma_{z^s}^2 + \rho_i^I \sigma_{z^a}^2 + \rho_i^I \sigma_{I_i}^2\right)^2}$, are non-positive. Furthermore, we rewrite constraints C1, C4, and C6 as

$$\text{C1}: \sum_{i=1}^{n_F} P_i|H_i|^2 gl\eta \geq \frac{P_{\min}^{req}}{\rho_1^E}, \quad (10)$$

$$\text{C4}: \rho_1^E = \rho_r^E, \forall r = \{2, \ldots, n_F\}, \quad \text{and} \quad (11)$$

$$\text{C6}: \rho_i^I + \rho_i^E = 1, \forall i, \quad (12)$$

respectively. Finally, we impose a non-negative value constraint on the auxiliary variables, C7: $\rho_i^I, \rho_i^E \geq 0, \forall i$. Hence, the constraints C1–C7 span a convex feasible solution set. Therefore, the problem with the approximated channel capacity (9) is jointly concave w.r.t. the optimization variables and traditional convex optimization techniques can be used for obtaining the

TABLE II
SYSTEM PARAMETERS

Receiver distance	10 meters
Multipath fading distribution	Rician fading (Rician factor 6 dB)
Carrier center frequency	470 MHz
Number of subcarriers n_F	128
Total bandwidth	20 MHz
Signal processing noise $\sigma_{z^s}^2$	-35 dBm
Antenna noise $\sigma_{z^a}^2$	-115 dBm
Channel path loss model	TGn path loss model
Lognormal shadowing g	1
Circuit power consumption P_C	40 dBm
Max. power grid supply P_G	50 dBm
Power amplifier power efficiency	$1/\varepsilon = 0.16$
Min. required power transfer $P_{\min}^{req}$	0 dBm
Energy harvesting efficiency η	0.8

solution. The Lagrangian of the transformed problem with the approximated objective function is given by

$$
\begin{aligned}
&\mathcal{L}(\lambda, \beta, \gamma, \boldsymbol{\mu}, \boldsymbol{\phi}, \mathcal{P}, \boldsymbol{\rho}) \\
&= \sum_{i=1}^{n_F} C_i - \lambda \Big(P_C + \sum_{i=1}^{n_F} \varepsilon P_i - P_{PG} \Big) - \sum_{r=2}^{n_F} \phi_r (\rho_1^E - \rho_r^E) \\
&\quad - \beta \Big(\sum_{i=1}^{n_F} P_i - P_{\max} \Big) - \gamma \Big(\frac{P_{\min}^{req}}{\rho_1^E} - \sum_{i=1}^{n_F} P_i |H_i|^2 g l \eta \Big) \\
&\quad - \sum_{i=1}^{n_F} \mu_i (\rho_i^I + \rho_i^E - 1),
\end{aligned}
\tag{13}
$$

where $\boldsymbol{\mu}$ and $\boldsymbol{\phi}$ are the Lagrange multiplier vectors with elements μ_i and ϕ_j which are associated with constraints C6 and C4, respectively. Therefore, the transmit power and the power splitting factor can be obtained as

$$
P_i^* = \left[\frac{W}{\ln(2)(\alpha + \beta - \gamma)} \right]^+, \forall i,
\tag{14}
$$

$$
\begin{aligned}
\rho_i^{I*} = &\left[\frac{\sqrt{\mu_i \sigma_{z^s}^2 \left(4W(\sigma_{z^a}^2 + \sigma_{I_i}^2) + \mu_i \sigma_{z^s}^2 \ln(2) \right)}}{2\mu_i (\sigma_{z^a}^2 + \sigma_{I_i}^2) \sqrt{\ln(2)}} \right. \\
&\left. - \frac{\sigma_{z^s}^2}{2(\sigma_{z^a}^2 + \sigma_{I_i}^2)} \right]^+, \forall i,
\end{aligned}
\tag{15}
$$

$$
\rho_r^{E*} = \left[\mu_r + \phi_r \right]^+, \forall r\{2, \dots, n_F\}, \quad \text{and}
\tag{16}
$$

$$
\rho_1^{E*} = \left[\frac{P_{\min}^{req} \gamma}{\mu_1 + \sum_{j=1}^{n_F} \phi_j} \right]^+.
\tag{17}
$$

The power allocation solution in (14) suggests that equal power allocation across different subcarriers is optimal in the high SINR regime. Moreover, P_i^* is decoupled from ρ_i^{I*} and, in contrast to suboptimal algorithm 1, iteration between P_i^* and ρ_i^{I*} is not required for obtaining the solution. Since the considered problem with the approximated objective function is jointly concave w.r.t. the optimization variables, the problem can be solved efficiently by finding the optimal Lagrange multipliers with numerical solvers [8].

V. SIMULATIONS

In this section, we evaluate the performance of the proposed power allocation algorithms using simulations. The simulation parameters can be found in Table II. For the optimal resource allocation algorithm, we use 1000 equally spaced intervals for quantizing the range of ρ_i for facilitating the full search. Besides, the maximum number of iterations $N_{\max}$ in suboptimal
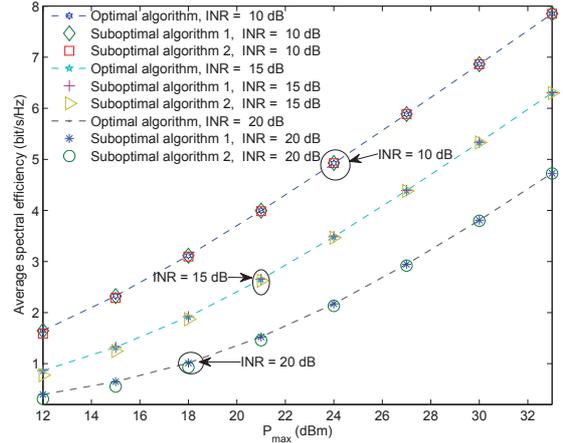
Fig. 2. Average system spectral efficiency (bit/s/Hz) versus maximum transmit power allowance, $P_{\max}$, for different levels of INR, $\frac{\sigma_{I_i}^2}{\sigma_{z^s}^2}$.

algorithm 1 is set to 5. Note that if the transmitter is unable to guarantee the minimum required power transfer $P_{\min}^{req}$, we set the system capacity for that channel realization to zero to account for the corresponding failure. For the sake of illustration, we define the interference-to-signal processing noise ratio (INR) as $\frac{\sigma_{I_i}^2}{\sigma_{z^s}^2}$.

A. Average System Spectral Efficiency

Figure 2 plots the average system spectral efficiency (bit/s/Hz) of the three proposed algorithms versus the maximum transmit power allowance, $P_{\max}$, for different INRs, $\frac{\sigma_{I_i}^2}{\sigma_{z^s}^2}$. It can be observed that the spectral efficiency of all algorithms increases with increasing $P_{\max}$. This is attributed to the fact that the transmitters in the algorithms radiate all the power available at the transmitter at every time instant whenever it is possible. Besides, an increasing amount of INR impairs the spectral efficiency of the system, despite the fact that part of the energy can be harvested by the receiver for satisfying the minimum required power transfer. On the other hand, suboptimal algorithm 1 performs very close to the optimal algorithm in all considered scenarios due to the iterative optimization. Besides, as expected, suboptimal algorithm 2 gives an excellent performance when $P_{\max}$ is large since it is asymptotically optimal in the high SINR regime. Yet, the performance of suboptimal algorithm 2 is less appealing in the low SINR regime, e.g. for INR = 20 dB and $P_{\max} < 18$ dBm, compared to the other two algorithms, due to the approximation of the objective function, cf. (14).

B. Average Harvested Power and Power Splitting Ratio

Figures 3 and 4 show, respectively, the average power splitting ratio, ρ_i, of the optimal algorithm and the two suboptimal algorithms versus maximum allowed transmit power, $P_{\max}$, for different levels of INR, $\frac{\sigma_{I_i}^2}{\sigma_{z^s}^2}$. For the optimal algorithm, it can be observed in Figure 3 that in all considered scenarios, the values of ρ_i increase w.r.t. to the maximum transmit power allowance $P_{\max}$. Although splitting more power for information decoding could also possibly increase the associated interference power, $\rho_i(\sigma_{z^a}^2 + \sigma_{I_i}^2)$, the power gain due to an increasing ρ_i in the signal strength of the desired signal, $\rho_i P_i |H_i|^2$, is able to counteract the performance impairment since the desired signal strength dominates the total received power. Besides, the slope of the curves depends heavily on the values of INRs and $P_{\max}$.
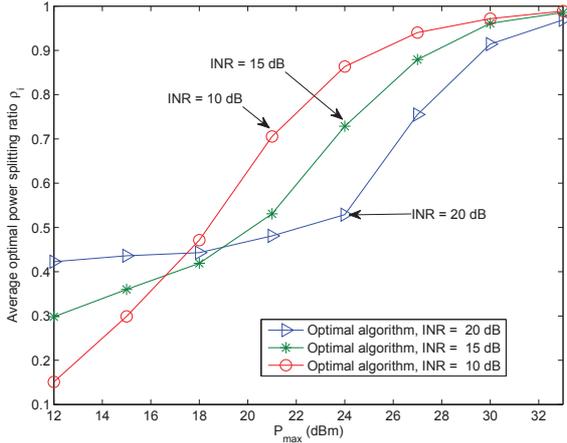
Fig. 3. Average optimal power splitting ratio, ρ_i, of the optimal algorithm versus the maximum transmit power allowance, $P_{\max}$, for different levels of INR, $\frac{\sigma^2_{I_i}}{\sigma^2_{z^s}}$.

Fig. 4. Average power splitting ratio, ρ_i, of the two suboptimal algorithms versus the maximum transmit power allowance, $P_{\max}$, for different levels of INR, $\frac{\sigma^2_{I_i}}{\sigma^2_{z^s}}$.

Indeed, the role of ρ_i is to balance the spectral efficiency caused by $\rho_i P_i |H_i|^2$ and the degradation caused by $\rho_i(\sigma^2_{z^a} + \sigma^2_{I_i})$ which results in a non-trivial trade-off between INR, $P_{\max}$, and ρ_i, cf. (2), (3). For instance, for a fixed small value of $P_{\max}$ (e.g. $P_{\max} < 18$ dBm), the average optimal value of ρ_i is higher for INR= 20 dB than for INR = 10 dB. Yet, for a fixed large value of $P_{\max}$ (e.g. $P_{\max} > 18$ dBm), the average optimal value of ρ_i is higher for INR= 10 dB than for INR = 20 dB. The detailed trade-off between these variables will be investigated in future work. On the other hand, Figure 4 shows that the values of ρ_i for the two suboptimal algorithms increase monotonically w.r.t. $P_{\max}$. In particular, both suboptimal algorithms have a higher preference for splitting more power for information decoding in the high INR regime. This is because the suboptimal algorithms only split enough power to satisfy the minimum required power transfer constraint C1 with equality (see Figure 5) and allocate the remaining power for information decoding.

Figure 5 reveals that, for the optimal algorithm, the average harvested power is a bell-shape function of the maximum transmit power allowance $P_{\max}$. Besides, the amount of harvested power is always larger than the minimum required power transfer $P^{req}_{\min}$. On the contrary, for the two suboptimal algorithms, the receivers only harvests just enough power for satisfying the minimum required power $P^{req}_{\min}$ which limits the power gain $P_i \rho_i$ in the channel capacity. Indeed, the two suboptimal algorithms both achieve a lower average system capacity and a lower average harvested power compared to the optimal algorithm. This is because the two suboptimal algorithms are not able to fully exploit the spectral efficiency gain achieved by $\rho_i P_i |H_i|^2$ and to reduce the degradation caused by $\rho_i(\sigma^2_{z^a} + \sigma^2_{I_i})$.

VI. CONCLUSIONS

In this paper, we formulated the power allocation algorithm design for simultaneous wireless information and power transfer in OFDM systems as a nonconvex optimization problem. The problem formulation took into account the minimum required power transfer for system capacity maximization. The problem was solved by a one-dimensional full search and convex optimization techniques which incurred a high complexity at the transmitter. Hence, two low-complexity suboptimal iterative algorithms were proposed to find a good compromise between computational complexity and system performance. Simula-
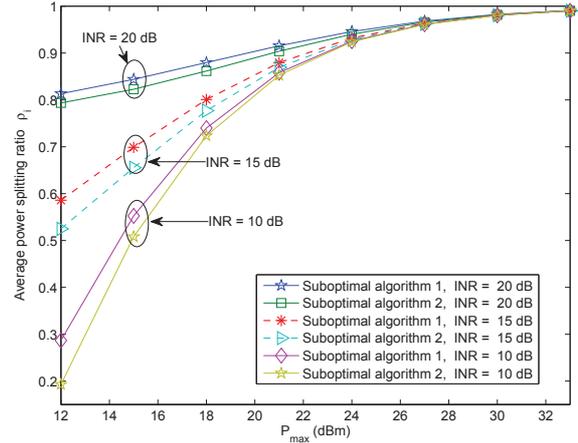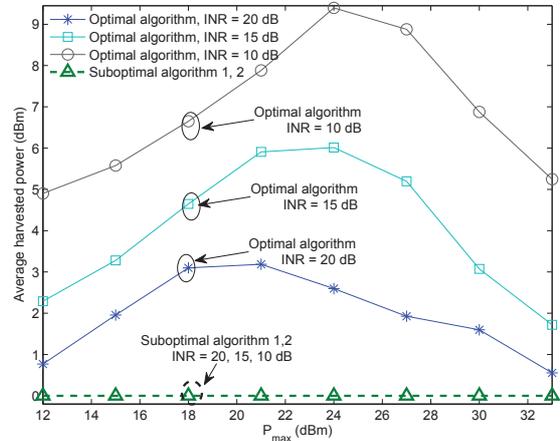
Fig. 5. Average harvested power (dBm) versus the maximum transmit power allowance, $P_{\max}$, for different levels of INR, $\frac{\sigma^2_{I_i}}{\sigma^2_{z^s}}$.

tion results illustrated that the proposed suboptimal algorithms achieved a close-to-optimal system capacity.

REFERENCES

[1] T. Chen, Y. Yang, H. Zhang, H. Kim, and K. Horneman, "Network Energy Saving Technologies for Green Wireless Access Networks," *IEEE Wireless Commun.*, vol. 18, pp. 30–38, Oct. 2011.
[2] D. W. K. Ng and R. Schober, "Energy-Efficient Power Allocation for M2M Communications with Energy Harvesting Transmitter," in *Proc. IEEE Global Telecommun. Conf.*, Dec. 2012.
[3] L. Varshney, "Transporting Information and Energy Simultaneously," in *Proc. IEEE Intern. Sympos. on Inf. Theory*, Jul. 2008, pp. 1612 –1616.
[4] P. Grover and A. Sahai, "Shannon Meets Tesla: Wireless Information and Power Transfer," in *Proc. IEEE Intern. Sympos. on Inf. Theory*, 2010, pp. 2363 –2367.
[5] R. Zhang and C. K. Ho, "MIMO Broadcasting for Simultaneous Wireless Information and Power Transfer," in *Proc. IEEE Global Telecommun. Conf.*, Dec. 2011, pp. 1 –5.
[6] X. Zhou, R. Zhang, and C. K. Ho, "Wireless Information and Power Transfer: Architecture Design and Rate-Energy Tradeoff," *submitted for possible journal publication*, 2012. [Online]. Available: http://arxiv.org/abs/1205.0618
[7] D. P. Bertsekas, *Nonlinear Programming*, 2nd ed. Athena Scientific, 1999.
[8] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge University Press, 2004.