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Green Radio

Taewon Hwang[1], Guowang Miao[2], Hyunsung Park[1], Younggap Kwon[1] and Nageen Himayat[3]

[1] *Yonsei University, Department of Electrical and Electronic Engineering, Seoul, Korea*
[2] *KTH Royal Institute of Technology, Communications Department, Stockholm, Sweden*
[3] *Intel Corporation, Intel Labs, Santa Clara, USA*

7.1 Energy-Efficient Design for Single-User Communications

Shannon theory provides some insights into the fundamental limits on minimum energy per bit required for reliable transmission for a single-user link. Based on the Shannon capacity formula, the data rate of an ideal band-limited additive white Gaussian noise (AWGN) channel is given as follows:

$$R = W \log_2 \left(1 + \frac{Pg}{WN_o}\right), \qquad [\text{bits/sec}]$$

where W is the channel bandwidth, P the transmission power, g the channel power gain, and N_o the noise spectral density. From a system-design perspective, g and N_o are usually given and W and P can be controlled by an appropriate transceiver design. To save energy, the transceiver should be designed to maximize the number of information bits reliably delivered per unit energy consumption, that is, the power should be chosen to maximize

$$u = \frac{W \log_2 \left(1 + \frac{Pg}{WN_o}\right) t}{Pt} = \frac{W \log_2 \left(1 + \frac{Pg}{WN_o}\right)}{P}, \quad [\text{bits/Joule}]$$

where t is the time used to send the bits, u is named the energy efficiency, with a unit bits/Joule. Note that choosing the power is the same as choosing the data rate and they are related through the power-rate function, for example, the Shannon capacity formula here. Therefore, another way formulating the problem is to write u as the function of the data rate R and the result

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should be the same. It can be easily proved that u decreases in P and the lowest power should be used. Therefore, the highest energy efficiency is achieved when $P \to 0$, that is, $R \to 0$ and infinitely long time should be used for data transmission, and

$$u^* = \lim_{P\to 0} \frac{W \log_2\left(1 + \dfrac{Pg}{WN_o}\right)}{P} = \frac{g}{N_0 \log 2}.$$

Similarly, if W is a variable, then u increases in W. The highest energy efficiency is achieved when $W \to \infty$, and

$$u^* = \lim_{W\to \infty} \frac{W \log_2\left(1 + \dfrac{Pg}{WN_o}\right)}{P} = \frac{g}{N_0 \log 2}.$$

In both of the aforementioned cases, the spectral efficiency is zero, indicating a trade-off between spectral and energy efficiency.

The ideal analysis above ignores channel impairment and practical issues such as delay spread, frequency selectivity of the channel, phase noise, nonlinearity of power amplifiers, and other wideband RF circuits. Furthermore, in addition to transmission power, a device will also incur additional circuit power that is relatively independent of the transmission rate [1, 2]. Thus a fixed energy cost of transmission is incurred, which must also be accounted for when designing energy-efficient transmission systems. In the following sections, we consider energy-efficient design for single-user transmission, accounting for the impact of circuit power. We first consider the case of flat fading wireless channels before addressing the more complex case of frequency-selective channels.

7.1.1 Energy-Efficient Transmission in Flat Fading Channels

To facilitate the understanding, we first consider a special case that the channel is experiencing flat fading. This happens in narrowband communications. We examine the basic relationship between energy efficiency and channel gain, circuit power, and system bandwidth. In this section, we investigate the optimal transmission power level maximizing the bits/Joule metric, accounting for the circuit power, P_c, consumed during transmission. The total energy consumption considering the circuit power is given as follows:

$$E = (P + P_c)t,$$

and the system energy efficiency is given as follows:

$$u(P) = \frac{W \log_2\left(1 + \dfrac{Pg}{WN_o}\right)}{P + P_c}.$$

It can be easily shown that u is strictly quasi-concave in P, as shown in Figure 7.1 [3]. For a strictly quasi-concave function, if a local maximum exists, it is also globally optimal. Besides, u is first strictly increasing and then strictly decreasing in P. Therefore, there is a

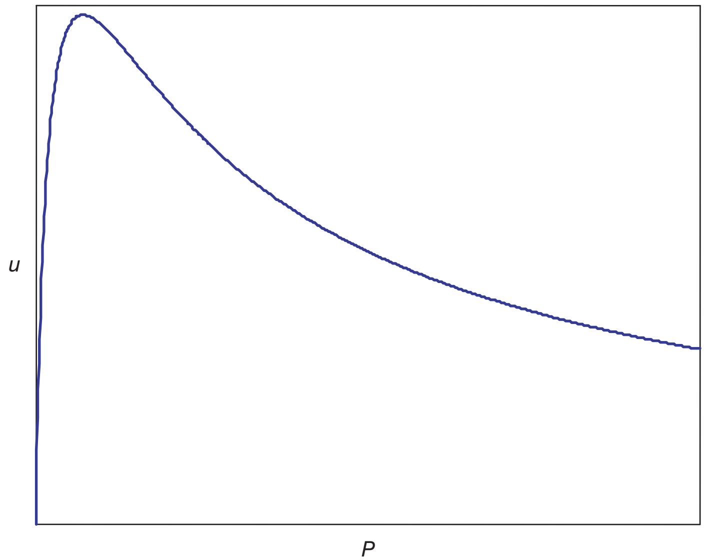

Figure 7.1 Quasi-concavity of the energy-efficiency function

unique optimal P^*, that is, a unique data rate R^*, that maximizes the energy efficiency and the first-order derivative of $u(P)$ at P^* is zero. P^* can be expressed as

$$P^* = \left(P^* + \frac{WN_0}{g}\right) \log\left(1 + \frac{P^* g}{WN_0}\right) - P_c.$$

In general, there is no closed-form expression of P^* and numeric methods such as the bisection method or the gradient assisted binary search (GABS) in [3] can be used to search for P^*. The basic idea of GABS is to first find a range that includes P^* and then use the bisection method to narrow down the range to the desired accuracy.

Further analyzing the energy-efficiency function, we can see that it increases with the bandwidth, W, indicating higher signal bandwidth can improve the transmitter energy efficiency. In a multiuser system, this means more system bandwidth should be allocated to users desiring energy efficiency [1].

It is shown in Ref. [3] that when the channel gain increases, higher transmission data rate should be used to improve energy efficiency. Furthermore, when the transmitter has a higher circuit power, higher transmission data rate should also be used. This is because with higher data rate, the duration the device has to be on can be decreased to reduce the circuit power consumption. When circuit power dominates power consumption, which is usually true with short-range communication, the highest data rate should be used to finish the transmission as soon as possible and then the device can be switched into a lower circuit power state, for example, sleep mode, as soon as possible. This technology has been commonly used in most medium access control (MAC) layer energy-efficient designs. When the circuit power is negligible, which is usually true with long-range communication such as satellite communications, the lowest data rate should be used, which coincides with the results in Refs. [4] and [5].

7.1.2 Energy-Efficient Transmission in Broadband Frequency-Selective Channels

Current communication systems design deals with frequency selectivity through subdividing the bandwidth into small segments, where the channel can assumed to be flat. So, for an ideal channel-orthogonalization technology such as MIMO or OFDM, the channel may be divided into K subchannels, each experiencing flat fading. Consider static channels to gain insights. The energy efficiency of such a system can be modeled by

$$u(\boldsymbol{R}) = \frac{\sum r_k}{P_T(\boldsymbol{R}) + P_c},$$

where $\boldsymbol{R} = [r_1, r_2, \ldots, r_K]$ is the data rate vector where r_k is the rate on the kth subchannel, $\sum r_k$ the total system throughput, and $P_T(\mathbf{R})$ the total transmission power consumed by the power amplifier for the reliable transmission of $\boldsymbol{R}$. Note that $P_T(\mathbf{R})$ characterizes all power consumption components that may vary depending on the data rate vector and P_c the remaining ones that are independent of $\boldsymbol{R}$. An example of the transmission power consumption for coded QAM system is [3]

$$P_T(\mathbf{R}) = \sum_{i=1}^{K} \left(e^{\frac{r_i}{W}} - 1 \right) \frac{N_0 W \mu}{g_i \gamma},$$

where μ is the SNR gap that defines the gap between the channel capacity and a practical coding and modulation scheme, and γ the power amplifier efficiency and depends on the design and implementation of the transmitter. It can be easily verified that $P_T(\boldsymbol{R})$ for almost all communication systems is strictly convex and monotonically increasing in $\boldsymbol{R}$ and in the following we make this assumption.

As shown in [3], $u(\boldsymbol{R})$ is strictly quasi-concave in $\boldsymbol{R}$. In addition, it is either strictly decreasing or first strictly increasing and then strictly decreasing in any r_i, that is, the local maximum of $u(\boldsymbol{R})$ for each r_i exists at either 0 or a positive finite value. For strictly quasi-concave functions, if a local maximum exists, it is also globally optimal. Hence, a unique globally optimal transmission rate vector always exists and the necessary and sufficient condition of the optimal $\boldsymbol{R}$ can be found by setting the first-order derivative of $u(\boldsymbol{R})$ to be zero. When each subchannel achieves the Shannon capacity, the optimal power allocation is a dynamic energy-efficient water-filling approach. With this approach, while the absolute value of power allocation is determined by the maximum energy efficiency $u(\boldsymbol{R}^*)$, which relies on both the circuit power and channel state, the relative differences of power allocations on different subchannels depend only on the channel gains on those subchannels.

The discussions above have not considered quality of service (QoS) assurance or resource constraints. If the global optimal transmission meets the QoS requirements and resource constraints, it can be used. Otherwise, the transmission should be adapted right on a subset of the boundary conditions and the optimality is guaranteed because of the strict quasi-concavity of the energy-efficiency function. Some examples of energy-efficient designs considering the constraints can be found in Refs. [3] and [6].

Similar to the energy-efficient transmission in flat fading channels, there are no closed-form expressions of the globally optimal transmission setting. Using appropriate approximation techniques, suboptimal closed-form link adaptation can be obtained. In Ref. [7], by using time-average energy efficiency, closed-form link adaptation is obtained with the knowledge of historical link energy efficiency in the past time slots and the performance is very close to the globally optimal one, depending on how fast the channel varies.

7.2 Energy-Efficient Design for Multiuser Communications

While it is important to investigate energy-efficient design for a single-link, wireless transmission is inherently multiuser in nature, with several mechanism defined for multiple access. Multiuser communications can simultaneously support a large number of users satisfying their QoS requirement, and therefore it significantly enhances the system performance as compared with single-user communications. In multiuser systems, the system resources must be divided among multiple users. For parallel transmission of symbols, multiuser MIMO allocates spatial degrees of freedom brought by the use of multiple antennas to multiple users, whereas OFDMA distributes subchannels obtained by dividing the entire bandwidth to multiple users. In cognitive radio, unlicensed secondary users can access the spectrum licensed to primary users by exploiting the idle times of the primary users. On the other hand, in cooperative systems multiple users can cooperate to enhance the transmissions of other users. In this section, we discuss energy-efficient designs of multiuser techniques such as multiuser MIMO, OFDMA, cognitive radio, and cooperative relay transmission.

7.2.1 Multiuser MIMO

For a single-user MIMO (SU-MIMO) system with M antennas at the base station (BS) and N antennas at the mobile user, the capacity gain is approximately $\min(M, N)$ times that of single-input single-output (SISO) systems [8]. In typical cellular systems, multiple antennas can be easily deployed at the BS, but the number of antennas at the mobile users is limited because of the size and cost constraints. Therefore, the capacity gain of SU-MIMO is usually limited by the number of antennas at the mobile user. An alternative to SU-MIMO is multiuser MIMO (MU-MIMO). In MU-MIMO systems, the BS serves multiple users simultaneously in the same frequency and time slots by spatially multiplexing the users' data using multiple antennas. The sum capacity of MU-MIMO grows linearly with $\min(M, nN)$, where n is the number of users served simultaneously, so an M-fold increase in the sum capacity can be obtained as long as nN is larger than M. When the number of users is larger than M, a scheduler can be employed to select up to M users. By opportunistically transmitting to the selected users having good channel conditions, multiuser diversity can be obtained [9]. Besides, by carefully allocating resources such as power, antennas, and subcarriers to the scheduled users, the performance of the MU-MIMO system can be improved. The user scheduling and the resource allocation can significantly improve the performance of MU-MIMO systems. In this subsection, we discuss user scheduling and resource allocation schemes to improve the energy efficiency of MU-MIMO systems.

We consider an energy-efficient user-scheduling problem in a downlink MU-MIMO system. With a zero-forcing precoder at the BS, the energy efficiency related to a user is given as:

$$u_i = \frac{\log_2\left(1 + \frac{\gamma_i P_{T_i}}{\sigma^2}\right)}{P_{T_i} + P_C},$$

where γ_i is the effective channel power gain from the BS to the user, P_{T_i} is the transmit power that the BS consumes for the user, σ^2 is the noise power, and P_C is the circuit power of the BS. Due to the zero-forcing precoder, γ_i of a user depends on the channels of the other scheduled users as well as its own channel. The user scheduler that maximizes the energy efficiency of the BS is given as follows:

$$S'_n = \underset{S_n \in \Omega}{\operatorname{argmax}} \sum_{i \in S_n} u_i,$$

where S_n is a set of scheduled users who are serviced simultaneously from the BS and Ω is the collection of all possible scheduled user sets. The number of possible scheduled user sets is $\binom{N_u}{k}$, where N_u is the number of all users and $k = |S_n| \leq M$ is the number of the scheduled users. Since the above scheduler does not consider the fairness, the cell-edge users, whose channel conditions are usually bad, are hardly selected.

Denote T_i to be the accumulated throughput for the ith user. The proportional-fair energy-efficient user scheduler

$$S'_n = \underset{S_n \in \Omega}{\operatorname{argmax}} \sum_{i \in S_n} \frac{u_i}{T_i},$$

can balance the cell-average energy efficiency and the cell-edge energy efficiency by increasing the priorities of the users that have been served less (with lower T_i) [10].

Now, we discuss energy-efficient power allocation. For a given set of scheduled users, $r_i = \log_2\left(1 + \frac{\gamma_i P_{T_i}}{\sigma^2}\right)$ is independent of the powers of the other scheduled users' due to the zero-forcing precoding at the BS and therefore, optimal P_{T_i} that maximizes $\sum_{i \in S_n} \frac{u_i}{T_i}$ is the one that maximizes $\frac{u_i}{T_i}$. Moreover, since r_i is strictly concave in P_{T_i} and $P_{T_i} + P_C$ is convex in P_{T_i}, u_i is strictly quasi-concave in P_{T_i} [11, 12]. Therefore, the optimal P_{T_i} is unique.

In an uplink MU-MIMO system where each user has multiple antennas, the energy efficiency of the users is written as

$$u = \frac{\sum_i \sum_k r_{ik}}{\sum_i \left(\sum_k P_{T_{ik}} + P_{a_i} + P_c\right)} \tag{7.1}$$

where r_{ik} and $P_{T_{ik}}$ are the data rate and transmit power for the kth stream of the ith user, respectively, P_{a_i} is the antenna-related circuit power consumption of the ith user, and P_c is the power consumption of circuit components that are independent of the antenna circuit operations. If the users use zero-forcing precoders and the BS uses a zero-forcing receiver, the data rate for the kth stream of the ith user is given as follows:

$$r_{ik} = \log_2\left(1 + \frac{\gamma_{ik} P_{T_{ik}}}{\sigma^2}\right),$$

where γ_{ik} is the equivalent channel power for the kth stream of the ith user and σ^2 is noise power. Since r_{ik} is a strictly concave function and sum of strictly concave functions is a strictly concave function, the numerator of u is also a strictly concave function. Similarly, the denominator of u is a convex function. Therefore, u is a strictly quasi-concave function of $\{P_{T_{ik}}\}$ and there exists a unique optimal $\{P_{T_{ik}}\}$ that maximizes u.

While using a large number of active antennas is always beneficial for increasing the spectral efficiency, it can decrease the energy efficiency because it requires more antenna-related circuit power consumption. Therefore, an improved circuit management scheme that can turn off circuit operations of the user-antennas whose energy efficiency is too low can improve the energy efficiency [13].

In some cases, the problem of maximizing energy efficiency can be solved more efficiently by using the Dinkelbach method [12]. When the numerator and the denominator of an objective function are concave and convex, respectively, the objective function can be transformed to an equivalent objective function in subtractive form which is a concave function. For example, the problem of maximizing the energy efficiency in Eq. (7.1) can be solved by the Dinkelbach method as follows. First, set $q = 0$ and calculate as:

$$P'_{T_{ik}} = \underset{P_{T_{ik}}}{\operatorname{argmax}} \sum_i \sum_k r_{ik} - q \sum_i \left(\sum_k P_{T_{ik}} + P_{a_i} + P_c \right).$$

Then, unless $\sum_i \sum_k r_{ik} - q \sum_i \left(\sum_k P'_{T_{ik}} + P_{a_i} + P_c \right) \approx 0$, update q by using the equation

$$q = \frac{\sum_i \sum_k r_{ik}}{\sum_i \left(\sum_k P'_{T_{ik}} + P_{a_i} + P_c \right)}.$$

This process repeats until $\sum_i \sum_k r_{ik} - q \sum_i \left(\sum_k P'_{T_{ik}} + P_{a_i} + P_c \right) \approx 0$.

In a MU-MIMO system, if the precoders and the receivers cannot fully eliminate the interference between users, the data rate of a user is affected by the powers of the other users as well as its own power. Moreover, the data rate of a user is not a concave function of transmit powers of all the users. In this case, the optimization problem is nonconvex and a brute force approach can be used to obtain a global optimal solution. By using some approximations, we can obtain a low-complexity suboptimal solution of the problem. For example, Ref. [14] considers a downlink MU-MIMO system where the BS adopts the MRT precoder. Since the object function is coupled and not concave, finding the optimal solution is difficult. For this reason, the energy efficiency is approximated to a lower bound which is a quasi-concave function. The problem of optimizing the quasi-concave energy efficiency function has been discussed above.

7.2.2 Orthogonal Frequency Division Multiple Access (OFDMA)

In OFDMA, the entire bandwidth is divided into a number of subchannels to transmit symbols for multiple users in a parallel fashion. By assigning each subchannel to the best user and adapting the rate and power according to its channel condition, the system throughput can be optimized. For these characteristics, OFDMA has been adopted by 4G standards such as 3GPP LTE and IEEE 802.16 WiMAX. In this subsection, we discuss adaptive subcarriers, power and rate allocation schemes for OFDMA to enhance the energy efficiency.

Consider an uplink OFDMA system in a flat fading channel. The energy efficiency of the ith user is given as follows:

$$u_i(c_i, P_{T_i}) = \frac{c_i \log_2 \left(1 + \frac{g_i P_{T_i}}{\sigma^2} \right)}{c_i P_{T_i} + P_c},$$

where c_i is the number of subcarriers allocated to the ith user, P_{T_i} is transmit power of the ith user on each subcarrier, g_i is the channel power gain of the ith user, σ^2 is the noise power, and P_c is the circuit power of the user.

For a given subcarrier allocation c_i to a user, the unique optimal power $P_{T_i}^*$ that maximizes u_i can be easily found because u_i is a quasi-concave function of P_{T_i}. Then, the optimal energy efficiency u_i^* and the corresponding rate r_i^* can be determined by using $P_{T_i}^*$. The optimal energy efficiency u_i^* increases with the channel power gain g_i. That is, if $g_i \leq g_j$ for $c_i = c_j$, then $u_i^* \leq u_j^*$ because

$$u_i^* = \frac{c_i \log_2\left(1 + \dfrac{g_i P_{T_i}^*}{\sigma^2}\right)}{c_i P_{T_i}^* + P_c} \leq \frac{c_j \log_2\left(1 + \dfrac{g_j P_{T_i}^*}{\sigma^2}\right)}{c_j P_{T_i}^* + P_c} \leq \frac{c_j \log_2\left(1 + \dfrac{g_j P_{T_j}^*}{\sigma^2}\right)}{c_j P_{T_j}^* + P_c} = u_j^*.$$

Also, since the energy efficiency of the ith user can be rewritten as

$$u_i = \frac{\log_2\left(1 + \dfrac{g_i P_{T_i}}{\sigma^2}\right)}{P_{T_i} + \dfrac{P_c}{c_i}},$$

increasing c_i is equivalent to decreasing the circuit power of the user. Therefore, energy efficiency increases with the number of allocated subcarriers. Since the number of total subcarrier is limited, $\sum_{\mathrm{i}} c_i \leq K$, a proper subcarrier allocation is required to maximize the sum energy efficiency of users. Consider a toy OFDMA system with two users and $K = 10$ subcarriers. As c_1 increases, u_1 also increases while u_2 decreases because $c_2 = 10 - c_1$ decreases. As shown in Figure 7.2, there exits optimal subcarrier allocation that maximizes the sum energy efficiency of users.

For a given power allocation, the optimal subcarrier allocation c_i's that maximize sum energy efficiency of users $\sum_{\mathrm{i}} u_i$ can be uniquely obtained because u_i is strictly concave in c_i and sum of strictly concave functions is a strictly concave function. An energy-efficient power and subcarrier allocation that can significantly improve the overall network energy efficiency is introduced in Ref. [1].

The above energy-efficient resource allocation for OFDMA can be extended to frequency-selective channels. In this case, dynamic power allocation across the subcarriers is required as well as power allocation across the users because even the subcarriers allocated to the same user experience different channel conditions. Each user's optimal power allocation across the subcarriers follows the water-filling algorithm, and the total power of a user should be determined to maximize its energy efficiency. Besides, the subcarrier allocation for the frequency-selective channel needs to decide which subcarriers are to be allocated to which users as well as the number of subcarriers to be allocated to each user. For these reasons, the subcarrier allocation for frequency-selective channels is much more complex in computation than that for flat fading channels. To reduce the complexity of subcarrier allocation, a suboptimal iterative subcarrier allocation that maximizes the minimum energy efficiency of a user rather than maximizing the system energy efficiency is proposed in Ref. [15].

If we use a nonexclusive subcarrier allocation, which allows allocating a subcarrier to more than one user, the performance of the OFDMA system can be further improved. However,

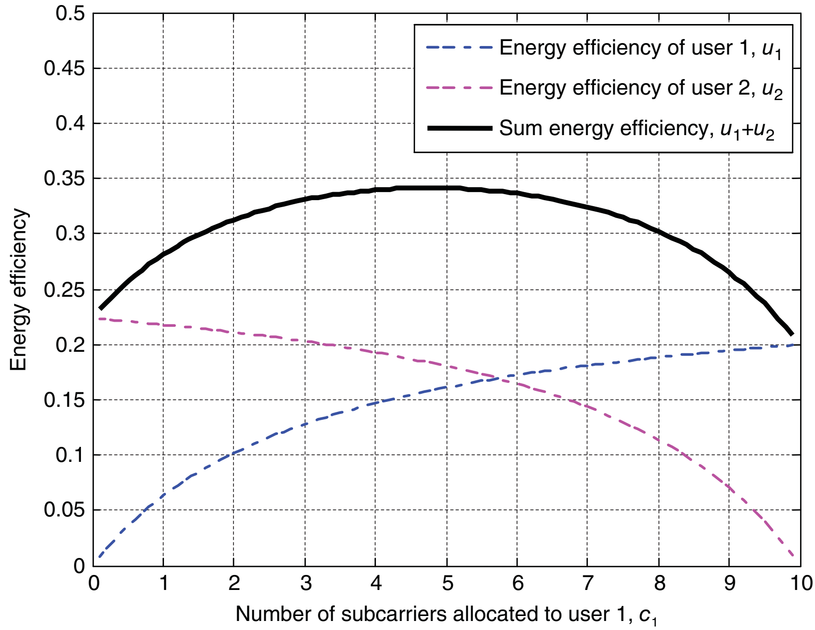

Figure 7.2 Sum energy efficiency of a two-user OFDMA system, $c_1 + c_2 = K = 10$

the nonexclusive subcarrier allocation makes the power and subcarrier allocation problem that maximizes sum energy efficiency of users to be coupled and nonconvex. Therefore, convex optimization techniques cannot be employed. In this case, a game-theoretic approach can be used. For example, Ref. [16] proposes a noncooperative game to obtain a low-complexity suboptimal energy-efficient power and subcarrier allocation. Here, the utility functions are chosen to satisfy the conditions of a potential game, which always admits Nash equilibrium [17]. The best response of each user can be found as follows. For a given subcarrier allocation, each user finds its optimal power that maximizes its utility. Each user can find the optimal subcarrier allocation that maximizes its utility function by the exhaustive search.

The above energy-efficient techniques for OFDMA systems assume perfect channel state information (CSI) and neglect the energy consumptions necessary for channel estimation. However, to be more precise, energy consumption in transmitting the pilot signals for channel estimation needs to be considered in the energy efficiency. Consider a downlink OFDMA system with M users and multiple subcarriers. Pilot symbols are periodically placed in the frequency domain and shared by the users. Denote α and β_i to be the pilot power and the data power of the ith user, respectively. The achievable rate of the ith user, C_i, is a function of pilot power α and its data power β_i [18]. The energy efficiency can be written as:

$$u = \frac{\sum_i C_i(\alpha, \beta_i)}{\alpha + \sum_i \beta_i + P_c},$$

where P_c is the circuit power at the BS. Cleary, the rate C_i increases as the pilot power α increase. Also, C_i is increasing in β_i. Our interest is to find α and β_i's that maximize u under the constraint of $\alpha + \sum_i \beta_i \leq P_{\max}$. It is shown in Ref. [18] that u is not jointly quasi-concave in α and β_i's, but u is quasi-concave with respect to $\alpha, \beta_1, \cdots \beta_M$,. In this case, a coordinate search that alternately finds optimal α and β_i's can be used [19].

7.2.3 Cognitive Radio

In the previous sections, we covered energy-efficient design for multiuser system wherein no specific spectrum access priority was assigned to users. However, cognitive radio (CR) is another potential key technology to increase the efficiency of spectrum utilization by allowing unlicensed secondary users (SUs) to access the spectrum licensed to primary users (PUs) as long as the QoS of the PUs is ensured [20]. There are two main spectrum access approaches in CR (1) opportunistic spectrum access [21, 22], where the SUs opportunistically access the spectrum when the PUs are inactive and (2) spectrum sharing [23, 24], where the SUs concurrently access the spectrum with the PUs provided that the interference to the PUs is kept below an acceptable level. In this subsection, we discuss the resource allocation techniques such as power control, beamforming, and spectrum allocation to increase the energy efficiency of the CR networks.

First, we consider an energy-efficient power control for a spectrum-sharing based CR network, where an SU network with K_s SU transmitters (SU-TXs) and one SU-receiver (SU-RX) coexists with a PU network consisting of K_p PU transmitters (PU-TXs) and one PU receiver (PU-RX). The transmit powers of the SU-TXs are constrained such that the maximum interference caused by all the SU-TXs to the PU-RX is below an acceptable level. The kth transmitter (among those $K_s + K_p$transmitters) sends bits at a common bit rate R in packets consisting of L information bits and $M - L$ overhead bits. In this case, the energy efficiency of the kth transmitter can be written as:

$$u_k(\mathbf{p}) = R\frac{L}{M}\frac{(1 - e^{\mathrm{SINR}(\boldsymbol{p})})^M}{p_k},$$

where $p_k \in [0, P_{k,\max}]$ is the transmit power of the kth transmitter, $\mathbf{p} = [p_1, \ldots, p_{K_p+K_s}]$ is transmit power vector, and $(1 - e^{\mathrm{SINR}(\boldsymbol{p})})^M$ is the probability that a packet is correctly received. Note that $P_{k,\max}$ is the transmit power limit if the kth transmitter is a PU-TX and the precalculated maximum allowed transmit power to ensure the QoS of the PUs if the kth transmitter is an SU-TX [25].

If each transmitter selfishly chooses its transmit power to maximize its energy efficiency based on its local information, the power control problem can be formulated as a noncooperative game represented by $\mathcal{G} = \left\{ \mathcal{K}, \left\{ \mathcal{S}_k \right\}_{k=1}^{K_p+K_s}, \ \{u_k\}_{k=1}^{K_p+K_s} \right\}$, where $\mathcal{K} = \{1, \ 2, \ldots, K_p + K_s\}$ is the set of players (PU-TXs and SU-TXs), $\mathcal{S}_k = [0, P_{k,\max}]$ is the set of the kth player's strategy (transmit power p_k), u_k is the kth player's utility (energy efficiency). The utility u_k can be shown to be strictly quasi-concave in p_k. If the utility function of each player is continuous in strategy vector $\mathbf{p}$ and quasi-concave in its strategy p_k, then the noncooperative game has at least one Nash equilibrium as long as the strategy set is compact and convex. Therefore, the above power control game has at least one Nash equilibrium. Moreover, the Nash equilibrium can be shown to be unique. Since u_k is strictly quasi-concave in p_k, the best response of the kth transmitter, or the p_k that maximizes u_k for a given set of other transmitters' powers is the minimum of (1) its power limit and (2) the power that satisfies $\frac{\partial u_k}{\partial p_k} = 0$. The best response function of this game can be shown to be a standard function [25]. A function $f(\mathbf{p})$ is standard if for all

$\mathbf{p} \geq \mathbf{0}$, it has (1) positivity: $f(\mathbf{p}) > 0$, (2) monotonicity: if $\mathbf{p} \geq \mathbf{p}'$, then $f(\mathbf{p}) > f(\mathbf{p}')$, and (3) scalability: For all $\alpha > 1$, $\alpha f(\mathbf{p}) > f(\alpha \mathbf{p})$, where the vector inequality $\mathbf{p} \geq \mathbf{p}'$ is an inequality in all components. If the best response of each player is a standard function, then the noncooperative game has a unique Nash equilibrium [26].

Next, we consider energy-efficient beamforming in a CR MU-MIMO system, where an SU-TX transmits messages to K SU-RXs sharing the spectrum with multiple pairs of PU-TX and PU-RX. The energy efficiency of the SU-TX is given by

$$u = \frac{\sum_{k=1}^{K} r_k}{\sum_{k=1}^{K} tr(\mathbf{A}_k \mathbf{A}_k^H) + P_c},$$

where $\mathbf{A}_k$ is the beamformer for the kth SU-RX, r_k is the rate of the kth SU-RX, and P_c is the circuit power at the SU-TX. The problem of finding the optimal $\mathbf{A}_k$'s that maximize u under the constraints on (1) maximum interference power to the PU-RXs, (2) maximum power of the SU-TX, and (3) the minimum throughput requirement is a nonconvex problem, and therefore hard to solve directly. We can construct an equivalent quasi-concave problem [27]. First, for a given power $p = \sum_{k=1}^{K} tr(\mathbf{A}_k \mathbf{A}_k^H)$ of the SU-TX, the optimal $\mathbf{A}_k$'s that maximize the system throughput $\sum_{k=1}^{K} r_k$ under the above constraints are found. Then, the energy efficiency u can be expressed as a function of p, that is,

$$u = \frac{R(p)}{p + P_c},$$

where $R(p)$ is the system throughput as a function of p. There is no closed-form expression of $R(p)$, but it can be shown that $R(p)$ is a concave function of p. Since a concave function divided by a convex function is quasi-concave, the energy efficiency u is a strictly quasi-concave function of p [11, 12]. In this case, the optimal p that maximizes u can be found numerically, for example, using the golden section method [27].

Now, we consider an energy-efficient spectrum and power allocation in a heterogeneous CR network that consists of a cognitive macro base station (MBS), multiple macro SUs (MSUs), and multiple femto base stations (FBSs). Each FBS is assumed to provide service to one femto SU (FSU). The cognitive MBS first purchases spectrum resources from multiple primary networks and then allocates the spectrum resources to MSUs and FBSs to maximize its revenue. The spectrum resource purchase and allocation problem can be formulated as a three-stage Stackelberg game. In Stage 1, the multiple primary networks perform a price competition game, where each primary network selfishly determines the spectrum selling price that maximizes its revenue. As shown in Ref. [28], the price competition game has a unique Nash equilibrium. In Stage 2, the cognitive MBS decides the bandwidth of the spectrum to purchase from each primary network, allocates the purchased spectrum to MSUs or FBSs, and performs energy-efficient power allocation for the MSUs to maximize its revenue. In Stage 3, each FBS performs power allocation that maximizes its energy efficiency. The energy efficiency of each FBS is shown to be strictly quasi-concave in its power [28]. Therefore, the optimal power of each FBS is the minimum of (1) its peak power and (2) a local maximizer of the energy efficiency. It is shown in Ref. [28] that the Stackelberg game has a unique Stackelberg equilibrium. The unique Stackelberg equilibrium can be numerically obtained by a gradient-based iterative algorithm in Ref. [28].

7.2.3.1 Cooperative Relay

In a cooperative relay system, relays assist the transmissions between sources and their corresponding destinations. With decode-and-forward (DF) protocol, each relay decodes the received signal, re-encodes the message bit, and then forwards the re-encoded signal. On the other hand, with amplify-and-forward (AF) protocol, each relay forwards the received signal with amplification only. Cooperative relaying can significantly enhance the network coverage and capacity because it reduces the path loss by shortening the transmission distances and enables cooperative diversity that mitigates the detrimental effect of fading in wireless networks [29]. This subsection considers enhancing the overall energy efficiency of relay systems. Natural questions are (1) what is optimal power control? (2) what is optimal number of relays to be used? and (3) what is optimal deployment of relays? In the following, we discuss energy-efficient designs in relay systems to answer these questions.

First, we consider a relay system where K relays using DF protocol are deployed in a serial fashion between a source and a destination. In the wideband regime, the data rate of the ith link is $r_i = \frac{ch_iP_i}{d_i^\alpha}$, where P_i is the transmit power of the ith link, d_i is the distance of the ith link, α is the path loss exponent, h_i is the small fading gain for the ith link, and c is a constant. The overall energy efficiency of the system is

$$u(\mathbf{P}, \mathbf{d}) = \frac{R(\mathbf{P}, \mathbf{d})}{\sum_{i=0}^{K} P_i + P_{c,\text{tot}}}, \tag{7.2}$$

where R is the overall data rate between the source and the destination, $\mathbf{P} = [P_0, \ldots, P_K]$, $\mathbf{d} = [d_0, \ldots, d_K]$, and $P_{c,\text{tot}}$ is the total circuit power dissipated by the source, the relays, and the destination. Since the nodes are serially concatenated, the overall rate R is dominated by the worst link, that is, $R = \min\limits_{0 \le i \le K} r_i$. Therefore, each node set its power $P_i = \frac{Rd_i^\alpha}{ch_i}$ to achieve $r_0 = \cdots = r_K = R$; otherwise, any node with higher power will waste its energy. For given link distances $\mathbf{d}$, the energy efficiency u increases with R, and maximizing u is equivalent to maximizing R [30]. Therefore, the worst link needs to transmit at its maximum allowable transmit power $P_{\max}$.

Now, we consider adjusting link distances $\mathbf{d}$ as well as link powers $\mathbf{P}$ to maximize the energy efficiency. For given link powers $\mathbf{P}$, the optimal link distances $\mathbf{d}^*(\mathbf{P}) = [d_0^*(\mathbf{P}), \ldots, d_K^*(\mathbf{P})]$ need to satisfy $R = r_0 = \cdots = r_k$. Inserting the obtained $\mathbf{d}^*(\mathbf{P})$ into Eq. (7.2), the energy efficiency $u(\mathbf{P}, \mathbf{d}(\mathbf{P}))$ can be shown to be strictly quasi-concave in $\mathbf{P}$ [3]. Therefore, each node uses the minimum of (1) its peak power and (2) the power at which the first-order derivative of $u(\mathbf{P}, \mathbf{d}(\mathbf{P}))$ is zero.

To study the relationship between the energy efficiency and the number of deployed relays, we consider the case of $h = h_0 = \cdots = h_K$. In this case, optimal transmit powers satisfy $P_0 = P_1 = \cdots = P_K$ and as shown in Ref. [30], the energy efficiency is increasing with P_0. Therefore, if there is no transmit power limits, each node transmits with infinite P_0. Then, the energy efficiency increases with the number of relays. The reason is as follows. The total energy consumption linearly increases with the number of relays. However, the achievable rate is exponentially increasing with the number of relays because (1) the link distances are inversely proportional to the number of relays and (2) the achievable data rate is exponentially decreasing with the link distances. Therefore, the energy efficiency increases as the number of relays increases when there is no transmit power limits.

Next, we consider energy-efficient power control in a relay network where an AF relay helps the transmissions of the multiple source–destination pairs. The multiple sources transmit at the same time using the same frequency band, and there exist interferences among the multiple source–destination pairs. Finding the optimal source powers that maximize the sum of the energy efficiencies of the sources is a coupled problem, and the tools of the convex optimization cannot be applied. In this case, the game-theoretic approach can be used. Assuming there is no cooperation between the sources, the source-power control problem can be formulated as a noncooperative power control game for the sources. In a noncooperative game, Nash equilibrium is a state where no player can improve its utility by changing only its own strategy unilaterally. It is shown in Ref. [31] that the power control game always has at least one Nash equilibrium. Moreover, when there is no direct links between sources and destinations, the Nash equilibrium is shown to be unique.

Besides, relay selection is another way to improve the energy efficiency of a relay system in a fading environment when there are multiple relays. The energy efficiency can be improved by opportunistically selecting the best relay among the multiple relays deployed. Some examples of energy-efficient relay selection schemes can be found in Refs. [32] and [33].

7.3 Summary and Future Work

This chapter has reviewed energy-efficient transmission and resource allocation techniques for wireless communications. First, the energy efficiency of the point-to-point AWGN channel was investigated from an information-theoretic perspective ignoring the circuit power. In this case, the energy efficiency strictly decreases in the transmit power, and therefore, the highest energy efficiency is achieved when the transmit power is zero. If the circuit power is considered, however, the energy efficiency is strictly quasi-concave in the transmit power. Therefore, there exists a unique nonzero optimal transmit power. In frequency-selective channels, OFDM can be employed to divide the entire bandwidth into multiple parallel subchannels, each experiencing flat fading. For a given total transmit power, maximizing the energy efficiency is equivalent to maximizing the spectral efficiency, whose solution is well known to be the water-filling algorithm. The total transmit power or the water level further needs to be adjusted to maximize the energy efficiency.

Besides, we have discussed the energy-efficient designs for the multiuser techniques such as MU-MIMO, OFDMA, cognitive radio, and cooperative relay transmission. In MU-MIMO, user scheduling is an important issue because it can significantly enhance the system performance by exploiting the multiuser diversity. For example, the energy-efficient proportional-fair user scheduling can balance the cell-average energy efficiency and the cell-edge energy efficiency. In OFDMA, energy-efficient subcarrier allocation schemes were investigated. If a user is allocated more subcarriers, the rate increases, but the power consumption also increases. Since the energy efficiency related to a user is strictly concave in the number of allocated subcarriers c_i, the optimal c_i is unique. If the subcarriers are allowed to be allocated nonexclusively to more than one user, interuser interference occurs. A noncooperative game was considered where each user selfishly chooses its subcarriers and powers to maximize its energy efficiency. If the utilities of the users are designed properly, the existence of Nash equilibrium can be guaranteed. In CR systems, secondary users should meet the QoS of primary users as well as improving their energy efficiencies. In a CR system where there are multiple secondary users, interuser interference occurs. In this case, a game-theoretic approach can be used, where each secondary user selfishly chooses its transmit power to maximize its own energy efficiency while protecting the QoS of the primary users. In cooperative relay systems, choosing the number of deployed relays and their locations is important as well as allocating powers to improve the energy efficiency. For a serially concatenated relay system, the performance bottleneck is the link with the worst SNR. Therefore, the optimal relay deployment and power allocation should ensure that all the links achieve the same data rate. If there is no transmit power limits, the energy efficiency increases with the number of relays deployed.

So far, many energy-efficient techniques have been proposed. However, there are still some important issues that need to be investigated. Most of the existing energy-efficient techniques for cellular system have considered only the single-cell environment. Extending the energy-efficient designs to multicell environments is important because multicell techniques can efficiently mitigate intercell interference and improve the system performance. Also, most of the energy-efficient OFDMA techniques considered only single antenna systems. However, OFDMA techniques can be combined with MIMO techniques to enhance the spectral efficiency. Therefore, energy-efficient MIMO-OFDMA techniques need to be investigated. Finally, most of the existing works on the energy-efficient design assumed perfect channel estimation and ignored the energy consumption for the channel estimation. To evaluate the energy efficiency more precisely, however, the energy consumed for the channel estimation needs to be considered.

References

Single-user references

[1] G. W. Miao, N. Himayat, Y. Li, and D. Bormann, "Energy-efficient design in wireless OFDMA," in Proc. IEEE ICC 2008, pp. 3307–3312, 2008.

[2] A. Y. Wang, S. Cho, C. G. Sodini, and A. P. Chandrakasan, "Energy efficient modulation and MAC for asymmetric RF microsensor system," in Int. Symp. Low Power Electronics and Design, Huntington Beach, CA, pp. 106–111, 2001.

[3] G. W. Miao, N. Himayat, and Y. Li, "Energy-efficient link adaptation in frequency-selective channels," IEEE Trans. Commun., vol. 58, no. 2, pp. 545–554, 2010.

[4] F. Meshkati, H. V. Poor, S. C. Schwartz, and N. B. Mandayam, "An energy-efficient approach to power control and receiver design in wireless networks," IEEE Trans. Commun., vol. 5, no. 1, pp. 3306–3315, 2006.

[5] B. Prabhakar, E. U. Biyikoglu, and A. E. Gamal, "Energy-efficient transmission over a wireless link via lazy packet scheduling," in Proc. IEEE Infocom 2001, Vol. 1, pp. 386–394, 2001.

[6] C. Xiong, G. Y. Li, S. Zhang, Y. Chen, and S. Xu, "Energy- and spectral-efficiency tradeoff in downlink OFDMA networks," IEEE Trans. Wireless Commun., vol. 10, no. 11, pp. 3874–3886, 2011.

[7] G. Miao, N. Himayat, G.Y. Li, S. Talwar, "Low-complexity energy-efficient scheduling for uplink OFDMA," IEEE Trans. Commun., vol. 60, no. 1, pp. 112–120, 2012.

Multiuser MIMO references

[8] D. N. C. Tse and P. Viswanath, Fundamentals of Wireless Communication. Cambridge, UK: Cambridge University Press, 2005.

[9] P. Viswanath, D. N. C. Tse, and R. Laroia, "Opportunistic beamforming using dumb antennas," IEEE Trans. Inf. Theory, vol. 48, no. 6, pp. 1277–1294, 2002.

[10] L. Liu, G. Miao, and J. Zhang, "Energy-efficient scheduling for downlink multi-user MIMO," in Proc. IEEE ICC 2012.

[11] S. Schaible, "Minimization of ratios," J. Opt. Theory Appl., vol. 19, no. 2, pp. 347–352, 1976.

[12] W. Dinkelbach, "On nonlinear fractional programming," Management Sci., vol. 13, pp. 492–498, 1967. Available: http://www.jstor.org/stable/2627691.

[13] G. Miao, "Energy-efficient uplink multi-user MIMO," IEEE Trans. Wireless Commun., vol. 12, no. 5, pp. 2302–2313, 2013.

[14] D. W. K. Ng, "Energy-efficient resource allocation in OFDMA systems with large numbers of base station antennas," IEEE Trans. Wireless Commun., vol. 11, no. 9, pp. 3292–3304, 2012.

OFDMA references

[15] C. Xiong, G. Y. Li, S. Zhang, Y. Chen, and S. Xu, "Energy-efficient resource allocation in OFDMA networks," IEEE Trans. Commun., vol. 60, no. 12, pp. 3767–3778, 2012.

[16] S. Buzzi, G. Colavolpe, D. Saturnino, and A. Zappone, "Potential games for energy-efficient power control and subcarrier allocation in uplink multicell OFDMA systems," IEEE J. Sel. Areas Commun., vol. 6, no. 2, pp. 89–103, 2012.

[17] D. Monderer and L. Shapley, "Potential games," J. Games Econ. Behav., vol. 14, no. 0044, pp. 124–143, 1996.

[18] Z. Xu, G. Y. Li, C. Yang, S. Zhang, Y. Chen, and S. Xu, "Energy-efficient power allocation for pilots in training-based downlink OFDMA systems," IEEE Trans. Commun., vol. 60, no. 10, pp. 3047–3058, 2012.

[19] J. C. Bezdek, R. J. Hathaway, R. E. Howard, C. A. Wilson, and M. P. Windham, "Local convergence analysis of a grouped variable version of coordinate descent," J. Optim. Theory Appl., vol. 54, no. 3, pp. 471–477, 1987.

Cognitive radio references

[20] J. Mitola, "Cognitive radio: an integrated agent architecture for software defined radio," Ph.D. Dissertation, KTH Royal Inst. of Technol., Stockholm, Sweden, 2000.

[21] S. Haykin, "Cognitive radio: brain-empowered wireless communications," IEEE J. Sel. Areas Commun., vol. 23, no. 2, pp. 201–220, 2005.

[22] Y.-C. Liang, Y. Zeng, E. C. Y. Peh, and A. T. Hoang, "Sensing-throughput tradeoff for cognitive radio networks," IEEE Trans. Wireless Commun., vol. 7, no. 4, pp. 1326–1337, 2008.

[23] T. A. Weiss and F. K. Jondral, "Spectrum pooling: an innovative strategy for the enhancement of spectrum efficiency," IEEE Commun. Mag., vol. 42, no. 3, pp. S8–S14, 2004.

[24] S. Choi, H. Park, and T. Hwang, "Optimal beamforming and power allocation for sensing-based spectrum sharing in cognitive radio networks," IEEE Trans. Veh. Technol. vol. 63, no. 1, pp. 412–417, 2014.

[25] S. Buzzi and D. Saturnino, "A game-theoretic approach to energy-efficient power control and receiver design in cognitive CDMA wireless networks," IEEE J. Sel. Topics Signal Process., vol. 5, no. 1, pp. 137–150, 2011.

[26] R. D. Yates, "A framework for uplink power control in cellular radio systems," IEEE J. Sel. Areas Commun., vol. 13, no. 7, pp. 1341–1347, 1995.

[27] J. Mao, G. Xie, J. Gao, and Y. Liu, "Energy efficiency optimization for cognitive radio MIMO broadcast channels," IEEE Commun. Lett., vol. 17, no. 2, pp. 337–340, 2013.

[28] R. Xie, F. R. Yu, H. Ji, and Y. Li, "Energy-efficient resource allocation for heterogeneous cognitive radio networks with femtocells," IEEE Trans. Wireless Commun., vol. 11, no. 11, pp. 3910–3920, 2012.

Relay references

[29] J. Laneman, D. Tse, and G. Wornell, "Cooperative diversity in wireless networks: efficient protocols and outage behavior," IEEE Trans. Inf. Theory, vol. 50, no. 12, pp. 3062–3080, 2004.

[30] G. Miao and A. Vasberg, “Energy efficiency in the wideband regime,” in Proc. IEEE WCNC 2013.
[31] A. Zappone, Z. Chong, E. A. Jorswieck, and J. Buzzi, “Energy-aware competitive power control in relay-assisted interference wireless networks,” IEEE Trans. Wireless Commun., vol. 12, no. 4, pp. 1860–1871, 2013.
[32] G. Lim and L. J. Cimini, Jr.,, “Energy-efficient cooperative relaying in heterogeneous radio access networks,” IEEE Wireless Commun. Lett., vol. 1, no. 5, pp. 476–479, 2012.
[33] O. Amin and L. Lampe, “Opportunistic energy efficient cooperative communication,” IEEE Wireless Commun. Lett., vol. 1, no. 5, pp. 412–415, 2012.