International Journal of Research in Engineering, Science and Management
Volume-1, Issue-12, December-2018
www.ijresm.com | ISSN (Online): 2581-5792

Optimal Energy Efficiency for 5G Wireless Communications

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***Abstract*: After about a decade of intense research, spurred by both economic and operational considerations, and by environmental concerns, energy efficiency has now become a key pillar in the design of communication networks. With the advent of the fifth generation of wireless networks, with millions more base stations and billions of connected devices, the need for energy-efficient system design and operation will be even more compelling. In this Paper we provides a minimization of the total power consumption while satisfying Quality of Service (QoS) constraints at the users and power constraints at the Base Station (BS) and Small Cell Access Points (SCA). To improve the cellular energy efficiency we analyze a combination of two densification approaches, namely "massive" multiple-input multiple-output (MIMO) base stations and small-cell access points with higher spatial reuse., we present resource-aware energy-saving technique with a low-complexity algorithm based on classical regularized zero-forcing (RZF) beamforming is proposed and compared with the optimal solution. Furthermore, we provide promising simulation results showing how the total power consumption can be greatly improved by combining massive MIMO and small cells; this is possible with both optimal and low-complexity beamforming.**

***Keywords*: Energy efficiency, 5G, resource allocation, dense networks, massive MIMO, small cells networks, mm Waves, RZF Beamforming, Base stations, small cell access points.**

1. Introduction

Energy consumption has become a primary concern in the design and operation of next generation wireless communication systems. Indeed, while for more than a century communication networks have been mainly designed with the aim of optimizing performance metrics such as the data-rate, throughput, latency, etc., in the last decade energy efficiency has emerged as a new prominent figure of merit, due to economic, operational, and environmental concerns. The design of the next generation (5G) of wireless networks will thus necessarily have to consider energy efficiency as one of its key pillars. Indeed, 5G systems will serve an unprecedented number of devices, providing ubiquitous connectivity as well as innovative and rate-demanding services. It is forecast that by 2020 there will be more than 50 billion connected devices [1], i.e. more than 6 connected devices per person, including not only human type communications, but also machine-type communications. The vision is to have a connected society in which sensors, cars, drones, medical and wearable devices will all use cellular networks to connect with one another, interacting with human end-users to provide a series of innovative services such as smart homes, smart cities, smart cars, tele surgery, and advanced security. Clearly, in order to serve such a massive number of terminals, future networks will have to dramatically increase the provided capacity compared to present standards. It is estimated that the traffic volume in 5G networks will reach tens of Exabyte's (10006 Bytes) per month. This requires the capacity provided by 5G networks to be 1000 times higher than in present cellular systems [2]. Trying to achieve this ambitious goal relying on the paradigms and architectures of present networks is not sustainable, since it will inevitably lead to an energy crunch with serious economic and environmental concerns. Economic Concerns: Current networks are designed to maximize the capacity by scaling up the transmit powers. However, given the dramatic growth of the number of connected devices, such an approach is not sustainable. Using more and more energy to increase the communication capacity will result in unacceptable operating costs. Present wireless communication techniques are thus simply not able to provide the desired capacity increase by merely scaling up the transmit powers. Environmental Concerns: Current wireless communication systems are mainly powered by traditional carbon-based energy sources. At present, information and communication technology (ICT) systems are responsible for 5% of the world's CO2 emissions [3], [4], but this percentage is increasing as rapidly as the number of connected devices. The classical macro-cell network topology is well-suited for providing wide-area coverage, but cannot handle the rapidly increasing user numbers and QoS expectations that we see today—the energy efficiency would be very low. The road forward s¬¬¬eems to be a densified topology that enables very high spatial reuse. Two main approaches are currently investigated: massive MIMO and small-cell networks. The first approach is to deploy large-scale antenna arrays at existing macro base stations (BSs) [1]. This enables precise focusing of emitted energy on the intended users, resulting in a much higher energy efficiency. The channel acquisition is indispensable for massive MIMO, which requires the exploitation of channel reciprocity using time-division duplex (TDD). This mode makes the channel estimation accuracy limited by the number of users and not the number of BS antennas [1]. The second approach is to deploy an overlaid layer of small-cell access points (SCAs) to offload traffic from BSs, thus exploiting the fact that most data traffic is localized and requested by low-mobility users. This approach reduces the average distance between users and transmitters, which translates into lower propagation losses and higher energy efficiency [2]. This comes at the price of having a highly heterogeneous network topology where it is difficult to control and coordinate inter-user interference. To meet this challenge, industry [3] and academia [4] are shifting focus from user-deployed femtocells to operator-deployed SCAs. The latter can rely on reliable backhaul connectivity and joint control/coordination of BS and SCAs; the existence of SCAs can even be transparent to the users, as in the soft-cell approach proposed for LTE in [3]. The total power consumption can be modeled with a static part that depends on the transceiver hardware and a dynamic part which is proportional to the emitted signal power [5]–[7]. Massive MIMO and small-cell networks promise great improvements in the dynamic part, but require more hardware and will therefore increase the static part. In other words, dense network topologies must be properly deployed and optimized to actually improve the overall energy efficiency. This paper analyzes the possible improvements in energy efficiency when the classical macro-cell topology is modified by employing massive MIMO at the BS and/or overlaying with SCAs. We assume perfect channel acquisition and a backhaul network that supports interference coordination; we thus consider an ultimate bound on what is practically achievable. The goal is to minimize the total power consumption while satisfying QoS constraints at the users and power constraints at the BS and SCAs. We show that this optimization problem has a hidden convex structure that enables finding the optimal solution in polynomial time. The solution is proved to automatically/ dynamically assign each user to the optimal transmitter (BS or SCA). A low-complexity algorithm based on classical regularized zero-forcing (RZF) beamforming is proposed an compared with the optimal solution. The potential merits of different densified topologies are analyzed by simulations.

2. System model

In order to avert the energy crunch, new approaches to wireless network design and operation are needed. The key point on which there is general consensus in the wireless academic and industry communities, is that the 1000_ capacity increase must be achieved at a similar or lower power consumption as today's networks [6], [7]. This means that the efficiency with which each Joule of energy is used to transmit information must increase by a factor 1000 or more. Increasing the network energy efficiency has been the goal of the Green Touch consortium [8], which was founded in 2010 as an open global pre-competitive research consortium with the focus to improve network energy efficiency by a factor 1000 with respect to the 2010 state of the art reference network. The consortium published a technology roadmap and announced its final results in its "Green Meter" research study [9].

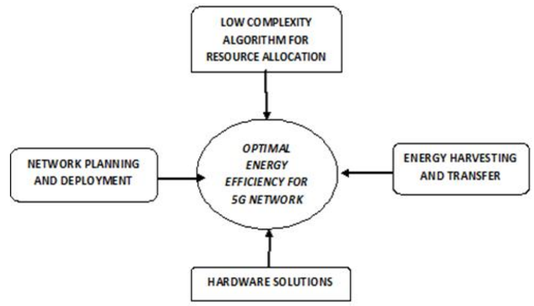

FIG:1 ENERGY EFFICIENT 5G TECHNOLOGIES

Fig. 1. Energy efficient 5G technologies

Additionally, the Groupe Speciale Mobile Association (GSMA) demands, by 2020, a reduction of CO2 emissions per connection of more than 40%. These fundamental facts have led to introducing the notion of bit-per-Joule energy efficiency, which is defined as the amount of information that can be reliably transmitted per Joule of consumed energy, and which is a key performance indicator for 5G networks [6],[7] (see also [10]–[12] as some of the first papers introducing the notion of bit-per-Joule energy efficiency). As illustrated in Fig. 1, most of the approach useful for increasing the energy efficiency of wireless networks can be grouped under four broad categories as follows.

Network planning and deployment: The second technique is to deploy infrastructure nodes in order to maximize the covered area per consumed energy, rather than just the covered area. In addition, the use of base station (BS) switch on/ switch-off algorithms and antenna muting techniques to adapt to the traffic conditions, can further reduce energy consumptions [14], [15].

Low Complexity Algorithm For Resource Allocation: The first technique to increase the energy efficiency of a wireless communication system is to allocate the system radio resources in order to maximize the energy efficiency rather than the throughput by using the low complexity algorithms. This approach has been shown to provide substantial energy efficiency gains at the price of a moderate throughput reduction [13].

Energy harvesting and transfer: The third technique is to operate communication systems by harvesting energy from the environment. This applies to both renewable and clean energy sources like sun or wind energy, and to the radio signals present over the air.

Hardware solutions: The fourth technique is to design the hardware for wireless communications systems explicitly accounting for its energy consumption [16], and to adopt major architectural changes, such as the cloud-based implementation of the radio access network [17]. In the following, a survey of the state-of-the-art relative to the above cited four categories is given, with a special focus on the papers published in this issue.

3. System analysis

A. Network planning and deployment

In order to cope with the sheer number of connected devices, several potentially disruptive technologies have been proposed for the planning, deployment, and operation of 5G networks. From that several technologies we use optimal soft cell coordination using Massive MIMO BS and Soft Cell Access points

B. Optimal Soft Cell Co-Ordination Method

We consider a single-cell downlink scenario where a macro BS equipped with NBS antennas should deliver information to K single-antenna users. In addition, there are S > 0 SCAs that form an overlay layer and are arbitrarily deployed. The SCAs are equipped with NSCA antennas each, typically 1 < NSCA, < 4, and characterized by strict power constraints that limit their coverage area (see below). In comparison, the BS has generous power constraints that can support high QoS targets in a large coverage area. The number of antennas, NBS, is anything from 8 to several hundred the latter means that NBS >>K and is known as massive MIMO. This scenario is illustrated in Fig. 2. The channels to user k are modeled as block fading. We consider a single flat-fading subcarrier where the channels are represented in the baseband by a $\mathbf{h}_{k,0}^{H} \in \mathbb{C}^{1\times N_{BS}}$ and $\mathbf{h}_{k,j}^{H} \in \mathbb{C}^{1\times N_{SCA}}$ for the BS and j[th] SCA, respectively. These are assumed to be perfectly known at both sides of each channel; extensions with robustness to channel uncertainty can be obtained as in [8]. The received signal at user k

$$y_k = \mathbf{h}_{k,0}^{H}\mathbf{x}_0 + \sum_{j=1}^{S} \mathbf{h}_{k,j}^{H}\mathbf{x}_j + n_k \qquad (1)$$

where x0 , xj are the transmitted signals at the BS and jth SCA, respectively. The term is the circularly symmetric complex Gaussian receiver noise with zero-mean and variance σ_k^2 , measured in mill watt (mW).

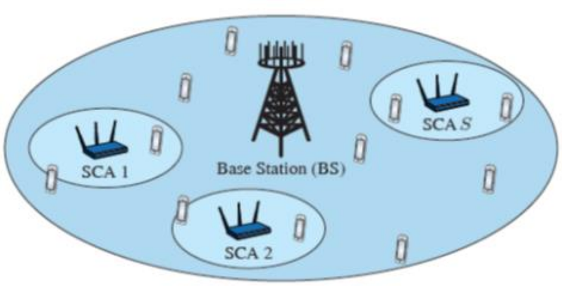

Fig. 2. Illustration of a downlink macro-cell overlaid with S small cells

The BS has NBS antennas and the SCAs have NSCA antennas. The K single antenna users (e.g., smartphones) can be served (non-coherently) by any combination of transmitters, but the circles indicate typical coverage areas.

The information symbols from the BS and the jth SCA to user k are denoted $x_{k,0}$ and $x_{k,j}$, respectively, and originate from independent Gaussian codebooks with unit power (in mW); that is, $x_{k,j}$ ~ CN(0; 1) for j = 0,….,S. These symbols are multiplied with the beamforming vectors $w_{k,0}=C^{Nbs*1}$ and $W_{k,j}$ (C^{NSCA*1} to obtain the transmitted signals

$$\mathbf{x}_j = \sum_{k=1}^{K} \mathbf{w}_{k,j} x_{k,j}, \quad j = 0, \ldots, S. \qquad (2)$$

The beamforming vectors are the optimization variables in this paper. Note that wk;j 6= 0 only for transmitters j that serve user k. This transmitter assignment is obtaine automatically and optimally from the optimization problem solved herein.

C. Problem Formulation

This paper considers minimization of the total power consumption while satisfying QoS constraints for each user. We will define both concepts before formulating the proble . The QoS constraints specify the information rate [bits/s/Hz] that each user should achieve in parallel. These are defined as is the aggregate signal-to-interference-and-noise ratio (SINR) of the kth user. The information rate log2(1 + SINRk) is achieved by applying successive interference cancellation on the own information symbols and treating co-user symbols as noise. Observe that this rate is obtained without any phase synchronization between transmitters, contrary to coherent joint transmission that requires very tight synchronization [10].

$\log_2(1+\mathrm{SINR}_k) \geq \gamma_k$, where γ_k is the fixed QoS target and

$$\mathrm{SINR}_k = \frac{|\mathbf{h}_{k,0}^{H}\mathbf{w}_{k,0}|^2 + \sum_{j=1}^{S} |\mathbf{h}_{k,j}^{H}\mathbf{w}_{k,j}|^2}{\sum_{\substack{i=1\\ i\neq k}}^{K} \left(|\mathbf{h}_{k,0}^{H}\mathbf{w}_{i,0}|^2 + \sum_{j=1}^{S} |\mathbf{h}_{k,j}^{H}\mathbf{w}_{i,j}|^2 \right) + \sigma_k^2} \qquad (3)$$

The power consumption (per subcarrier) can be modeled as $P_{dynamic} + P_{static}$ [5]–[7] with the dynamic and static terms given by below

$$P_{\text{dynamic}} = \rho_0 \sum_{k=1}^{K} \|\mathbf{w}_{k,0}\|^2 + \sum_{j=1}^{S} \rho_j \sum_{k=1}^{K} \|\mathbf{w}_{k,j}\|^2, \qquad (4)$$

$$P_{\text{static}} = \frac{\eta_0}{C} N_{\text{BS}} + \sum_{j=1}^{S} \frac{\eta_j}{C} N_{\text{SCA}}, \qquad (5)$$

The dynamic term is the aggregation of the emitted powers $\sum_{k=1}^{K} \|\mathbf{w}_{k,j}\|^2$, each multiplied with a constant P_j >1 accounting for the inefficiency of the power amplifier at this transmitter. The static term, P_{static}, is proportional to the number of antennas and $N_j \geq 0$ models the power dissipation in the circuits of each antenna (e.g., in filters, mixers, converters, and baseband processing). P_{static} is normalized with the total number of subcarriers C $\geq$ 1. Representative numbers on these parameters are given in Table I, [6], and [11] Each BS and SCA is prone to Lj power constraints

$$\sum_{k=1}^{K} \mathbf{w}_{k,j}^{H} \mathbf{Q}_{j,\ell} \mathbf{w}_{k,j} \leq q_{j,\ell}, \quad \ell = 1, \ldots, L_j. \qquad (6)$$

The weighting matrices given by below are positive and semi definite. $\mathbf{Q}_{0,\ell} \in \mathbb{C}^{N_{\text{BS}}\times N_{\text{BS}}}$, $\mathbf{Q}_{j,\ell} \in \mathbb{C}^{N_{\text{SCA}}\times N_{\text{SCA}}}$ for j =

International Journal of Research in Engineering, Science and Management
Volume-1, Issue-12, December-2018
www.ijresm.com | ISSN (Online): 2581-5792

1,….,s.The corresponding limits are qj; _ 0. The parameters $Q_{j,k,l}$ are fixed and can describe any combination of per-antenna, per-array, and soft shaping constraints [10]. We typically have q_{ol} >> $q_{j.l}$ for 1 $\leq$ j $\leq$ S, because the BS provides coverage. Our numerical evaluation considers per-antenna constraints of qj [mW] at the j^{th} transmitter, given by $L_0 = N_{BS}$, Lj = N_{SCA}, $q_{j,l}$ = $q_{j\wedge l}$`with one at `the diagonal element and zero elsewhere. We are now ready to formulate our optimization problem. We want to minimize the total power consumption while satisfying the QoS constraints and the power constraints,

$$\begin{aligned} \underset{\mathbf{w}_{k,j}\ \forall k,j}{\text{minimize}} \quad & P_{\text{dynamic}} + P_{\text{static}} \\ \text{subject to} \quad & \log_2(1+\text{SINR}_k) \geq \gamma_k \quad \forall k, \\ & \sum_{k=1}^{K} \mathbf{w}_{k,j}^H \mathbf{Q}_{j,\ell} \mathbf{w}_{k,j} \leq q_{j,\ell} \quad \forall j,\ell. \end{aligned} \tag{7}$$

In the next section, we will prove that (7) can be reformulated as a convex optimization problem and thus is solvable in polynomial time using standard algorithms. Moreover, the optimal power-minimizing solution is self-organizing in the sense that only one or a few transmitters will serve each user.

D. Low complexity algorithm for resource allocation

This section derives algorithms for solving the optimization problem (7). The QoS constraints in (7) are complicated functions of the beamforming vectors, making the problem non-convex in its original formulation. However, we will prove that it has an underlying convex structure that can be extracted using semi-definite relaxation. We generalize the original approach in [12] to spatial multiflow transmission.

To achieve a convex reformulation of (7), we use the notation matrix should be positive semi-definite, denoted as Wk;j $\leq$ 0, and have rank (Wk;j) $\leq$ 1. Note that the rank can be zero, which implies that Wk;j = 0. By including the BS and SCAs in the same sum expressions, we can rewrite (7) compactly as

$$\begin{aligned} \underset{\mathbf{W}_{k,j}\succeq \mathbf{0}\ \forall k,j}{\text{minimize}} \quad & \sum_{j=0}^{S} \rho_j \sum_{k=1}^{K} \text{tr}(\mathbf{W}_{k,j}) + P_{\text{static}} \\ \text{subject to} \quad & \text{rank}(\mathbf{W}_{k,j}) \leq 1 \quad \forall k,j, \\ & \sum_{j=0}^{S} \mathbf{h}_{k,j}^H \left(\left(1+\frac{1}{\bar{\gamma}_k}\right) \mathbf{W}_{k,j} - \sum_{i=1}^{K} \mathbf{W}_{i,j} \right) \mathbf{h}_{k,j} \geq \sigma_k^2 \quad \forall k, \\ & \sum_{k=1}^{K} \text{tr}(\mathbf{Q}_{j,\ell} \mathbf{W}_{k,j}) \leq q_{j,\ell} \quad \forall j,\ell, \end{aligned} \tag{8}$$

The optimal beamforming for spatial soft-cell coordination can be computed in polynomial time using Theorem 1. This complexity is relatively modest, but the algorithm becomes infeasible for real-time implementation when NBS and S grow large. In addition, Theorem 1 provides a centralized algorithm that requires all channel knowledge to be gathered at the BS.

Theorem 1 should be seen as the ultimate benchmark when evaluating low-complexity algorithms for non-coherent coordination. To demonstrate the usefulness, we propose the low-complexity non-iterative Multiflow-RZF beamforming**:**

1) Each transmitter $j = 0, \ldots, S$ computes

$$\mathbf{u}_{k,j} = \frac{\left(\sum_{i=1}^{K} \frac{1}{\sigma_i^2} \mathbf{h}_{i,j}\mathbf{h}_{i,j}^H + \frac{K}{\bar{\gamma}_k q_j}\mathbf{I}\right)^{-1} \mathbf{h}_{k,j}}{\left\| \left(\sum_{i=1}^{K} \frac{1}{\sigma_i^2} \mathbf{h}_{i,j}\mathbf{h}_{i,j}^H + \frac{K}{\bar{\gamma}_k q_j}\mathbf{I}\right)^{-1} \mathbf{h}_{k,j} \right\|} \quad \forall k,$$

$$g_{i,k,j} = |\mathbf{h}_{i,j}^H \mathbf{u}_{k,j}|^2 \quad \forall i,k, \quad Q_{j,\ell,k} = \mathbf{u}_{k,j}^H \mathbf{Q}_{j,\ell} \mathbf{u}_{k,j} \quad \forall \ell,k.$$

2) The jth SCA sends the scalars $g_{i,k,j}, Q_{j,\ell,k}\ \forall k,i,\ell$ to the BS. The BS solves the convex optimization problem

$$\begin{aligned} \underset{p_{k,j}\geq 0\ \forall k,j}{\text{minimize}} \quad & \sum_{j=0}^{S} \rho_j \sum_{k=1}^{K} p_{k,j} + P_{\text{static}} \\ \text{subject to} \quad & \sum_{k=1}^{K} Q_{j,\ell,k} p_{k,j} \leq q_{j,\ell} \quad \forall j,\ell, \\ & \sum_{j=0}^{S} p_{k,j} g_{k,k,j} \left(1+\frac{1}{\bar{\gamma}_k}\right) - \sum_{i=1}^{K} p_{i,j} g_{k,i,j} \geq \sigma_k^2 \quad \forall k. \end{aligned} \tag{9}$$

3) The power allocation $p_{k,j}^*\ \forall k$ that solves (9) is sent to the jth SCA, which computes $\mathbf{w}_{k,j} = \sqrt{p_{k,j}^*}\mathbf{u}_{k,j}\ \forall k$.

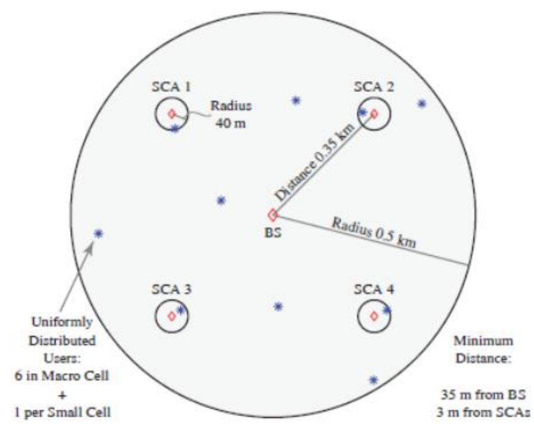

Fig. 3. The single-cell scenario analyzed in Section 4

The BS and SCAs are fixed, while the 10 users are randomly distributed as described above. This algorithm applies the heuristic RZF beamforming (see e.g., [2]) to transform (7) into the power allocation problem which has the same low complexity irrespectively of the number of antennas. The algorithm is non-iterative, but some scalar parameters are exchanged between the BS and SCAs to enable coordination. In practice, only users in the vicinity of an SCA are affected by it, thus only a few parameters are exchanged per SCA while all other parameters are set to zero.

E. Energy harvesting and transfer

Harvesting energy from the environment and converting it to electrical power is emerging as an appealing possibility to operate wireless communication systems. Indeed, although this approach does not directly reduce the amount of energy required to operate the system, it enables wireless networks to be powered by renewable and clean energy sources [11]. Two main kinds of energy harvesting have emerged so far in the context of wireless communications. Environmental energy harvesting: This technique refers to harvesting clean energy from natural sources, such as sun and wind. Comprehensive surveys on this approach are [12] and [13]

Radio-frequency energy harvesting: This technique refers to harvesting energy from the radio signals over the air, thus enabling the recycling of energy that would otherwise be wasted. In this context, interference signals provide a natural source of electromagnetic-based power. Surveys on this approach are [14] and [15]. The main challenge in the design of communication systems powered by energy harvesting is the random amount of energy available at any given time. This is due to the fact that the availability of environmental energy sources (e.g. sun or wind) is inherently a stochastic process, and poses the problem of energy outages. Unlike traditionally-powered networks, communication systems powered by energy harvesting must comply with the so-called energy causality constraint, i.e. the 7 energy used at time t cannot exceed the energy harvested up to time t. Early works on environmental energy harvesting dealt with this problem by taking a so-called off-line approach, assuming that the amount of energy harvested at a given point in time is known in advance. Although difficult to meet in practice, this approach provides insight as to the ultimate performance of energy-harvesting systems. In [56] an offline power allocation algorithm termed directional waterfilling is proposed, while [57] addresses a similar problem but assuming a system in which the data to be transmitted is available at random times. In [58] and [59], the results of [57] are extended to the more realistic case of a battery with finite capacity, while the impact of energy leakages due to non-ideal batteries is considered in [60]. Previous results have been extended to multi-user networks in [61] and [62], to relay-assisted communications in [23], and to multiple-antenna systems [24]. More recently, research efforts have been aimed at overcoming the off-line approach, developing on-line design policies, which do not assume any knowledge about the amount of energy harvested at specific times. Two main approaches have emerged in this context. Tools from stochastic optimization are used to develop design protocols assuming that the statistics of the energy process are known [25]–[27]. Alternatively, approaches based on learning theory provide the means to design energy. The issue of energy randomness is also present as far as radio-frequency energy harvesting is concerned, because in general the amount of electromagnetic power available in the air is not known in advance. Indeed, several schemes have appeared in the literature in which a node opportunistically exploits the electromagnetic radiation over the air. In [30] an OFDMA system is considered, in which a hybrid BS is considered, which is partly powered by radio frequency energy harvesting. In [31] and [32] a relay-assisted network is considered, wherein the relay is powered by drawing power from the received signals. A cognitive radio system is considered in [33], in which the secondary network draws energy from the signals received from the primary network. However, radio-frequency energy harvesting offers an intriguing possibility, which also helps to reduce the randomness of wireless power sources. The idea is to combine energy harvesting with wireless power transfer techniques, thereby enabling network nodes to share energy with one another [34]. This has a two-fold advantage. First, it makes it possible to redistribute the network total energy, prolonging the lifetime of nodes that are low on battery energy [35], [36]. Second, it is possible to deploy dedicated beacons in the network, which act as wireless energy sources, thereby elimination or reducing the randomness of the radio-frequency energy source. This approach can be taken even further, superimposing the energy signals on regular communication signals, resulting in the so called simultaneous wireless information and power transfer (SWIPT) [37]–[39]. Several contributions to wireless power transfer are included in this special issue [40]–[42]. In [40], SWIPT in nonorthogonal multiple access networks is considered. The network nodes are assumed to be spatially randomly located over the covered area and a novel protocol is provided in which users close to the source act as energy harvesting relays to help faraway users. In 141], the co-existence of a MISO femtocell system with a macro-cell system is considered. The femtocell simultaneously transmits information to some of its users and energy to the rest of its users, while also suppressing its interference to macro-cell devices. The system energy efficiency is maximized with respect to the system beamforming vectors by means of fractional programming theory. In [42], energy harvesting and wireless power transfer is studied in relay-assisted systems with distributed beamforming, proposing a novel power splitting strategy.

F. Hardware solutions

Energy-efficient hardware solutions refers to a broad category of strategies comprising the green design of the RF chain, the use of simplified transmitter/receiver structures, and, also, a novel architectural design of the network based on a cloud implementation of the radio access network (RAN) and on the use of network function virtualization. Attention has been given to the energy-efficient design of power amplifiers [143], [144], both through direct circuit design and through signal design techniques aimed at peak-to-average-power ratio reduction. The use of simplified transmitter and receiver architectures, including the adoption of coarse signal quantization (e.g. one bit quantization) and hybrid analog/digital beamformers, is another technique that is being proposed for increasing hardware energy efficiency, especially in systems with many antennas such as massive MIMO systems and mmWave systems. The paper [45], as an instance, presents an analysis of the spectral efficiency of single-carrier and OFDM transmission in massive MIMO systems that use one-bit analog-to-digital converters (ADCs), while a capacity analysis of one-bit quantized MIMO systems with transmitter CSI is reported in [46]. One-bit ADCs coupled with high-resolution ADCs are instead proposed and analyzed in the paper [47], from this special issue, to simplify receiver design in massive MIMO systems. The paper shows that the proposed

International Journal of Research in Engineering, Science and Management
Volume-1, Issue-12, December-2018
www.ijresm.com | ISSN (Online): 2581-5792

mixed-ADC architecture with a relatively small number of high-resolution ADCs is able to achieve a large fraction of the channel capacity of the conventional architecture, while reducing the energy consumption considerably even compared with antenna selection strategies, for both single-user and multi-user scenarios. For mmWave communications, given the required large number of antenna elements, the implementation of digital beamforming poses serious complexity, energy consumption, and cost issues. Hybrid analog and digital beamforming structures have been thus proposed as a viable approach to reduce complexity and, most relevant to us, energy consumption [14], [15], [49]. The paper [50], in this special issue, focuses on a mmWave MIMO link with hybrid decoding. Unlike previous contributions on the subject, which considered a fully-connected architecture requiring a large number of phase shifters, a more energy-efficient hybrid precoding with sub-connected architecture is proposed and analyzed in conjunction with a successive interference cancellation (SIC) strategy. The paper also shows through simulation results that the proposed SIC-based hybrid precoding is near-optimal and enjoys higher energy efficiency than spatially sparse precoding [51] and fully digital precoding. Cloud-based implementation of the RAN is another key technology instrumental to making future 5G networks more energy-efficient. Spurred by the impressive spread of cloud computing, cloud-RAN (C-RAN) is based on the idea that many functions that are currently performed in the BS, can be actually transferred to a remote data-center and implemented via software [17], [52], [53]. The most extreme implementation of C RAN foresees light BSs wherein only the RF chain and the baseband-to-RF conversion stages are present; it is assumed that these light BSs are connected through high capacity links to the data-center, wherein all the baseband. Processing and the resource allocation algorithms are run. This enables a great deal of flexibility in the network, thus leading to substantial savings as far as both deployment costs and energy consumption are concerned. Mobile-edge computing [154] is also a recently considered approach that increases network flexibility potentially leading to considerable energy savings. The studies [55]–[58] are a sample of the many recent works that have addressed the energy-efficiency gains possible with a cloud-based RAN. In this special issue, paper [159] investigates the role that cellular traffic dynamics play in efficient network energy management, and designs a framework for traffic-aware energy optimization. In particular, using a learning approach, it is shown that the C-RAN can be made aware of the near-future traffic, so that inactive or low-load BSs can be switched off, thus reducing the overall energy consumption. The proposed approach is also validated on real traffic traces and energy savings on the order of 25% are achieved. The paper [160], from this special issue, proposes a holistic sparse optimization framework to design a green C-RAN by taking into consideration the power consumption of the fronthaul links, multicast services, as well as user admission control. Specifically, the sparsity structures in the solutions of both the network power minimization and user admission control problems are identified, which call for adaptive remote radio head (RRH) selection and user admission, a problem that is solved through a nonconvex but smoothed `p minimization (0 < p _ 1) approach to promote sparsity in the multicast setting. Finally, [16], again from this special issue, studies the energy efficiency of a downlink C-RAN, focusing on two different downlink transmission strategies, namely the data-sharing strategy and the compression strategy. The paper shows that C-RAN signicantly improves the range of feasible user data rates in a wireless cellular network, and that both data-sharing and compression strategies bring much improved energy efficiency to downlink C-RAN as compared to nonoptimized Coordinated Multipoint (CoMP)

4. Numerical evaluation and simulation results

This section illustrates the analytic results and algorithms of this paper in the scenario depicted in Fig. 3. This figure shows a circular macro cell overlaid by 4 small cells. There are 10 active users in the macro cell, whereof 6 users are uniformly distributed in the whole cell and each SCA has one user uniformly distributed within 40 meters. We evaluate the average performance over user locations and channel realizations. Table I shows the hardware parameters that characterize the power consumption and is based on [6, Table 7] and [11].

TABLE I
HARDWARE PARAMETERS IN THE NUMERICAL EVALUATION

Parameters	Values
Efficiency of power amplifiers	$\frac{1}{\rho_0} = 0.388$, $\frac{1}{\rho_j} = 0.052\ \forall j$
Circuit power per antenna	$\eta_0 = 189$ mW, $\eta_j = 5.6$ mW $\forall j$
Per-antenna constraints	$q_{0,\ell} = 66$, $q_{j,\ell} = 0.08$ mW $\forall j, \ell$

TABLE II
CHANNEL PARAMETERS IN THE NUMERICAL EVALUATION

Parameters	Values
Macro cell radius	0.5 km
Carrier frequency / Number of subcarriers	$F = 2$ GHz / $C = 600$
Total bandwidth / Subcarrier bandwidth	10 MHz / 15 kHz
Small-scale fading distribution	$\mathbf{h}_{k,j} \sim \mathcal{CN}(\mathbf{0}, \mathbf{R}_{k,j})$
Standard deviation of log-normal shadowing	7 dB
Path and penetration loss at distance d (km)	$148.1+37.6\log_{10}(d)$ dB
Special case: Within 40 m from SCA	$127+30\log_{10}(d)$ dB
Noise variance σ_k^2 (5 dB noise figure)	-127 dBm

The channels are modeled similarly to Case 1 for Heterogeneous deployments in the 3GPP LTE standard [16], but the small-scale fading is modified to reflect recent works on massive MIMO. We assume Rayleigh small-scale fading: hk,j < CN(0;Rk,j). The correlation matrix is spatially uncorrelated, Rk,j / I, between the jth SCA and each user k. The correlation matrix between the BS and each user is modeled according to the physical channel model where the main characteristics are antenna correlation and reduce drank channels. Note that the propagation loss is different for BS and SCAs; see Table II for all channel model parameters. We first analyze the impact of having different number of antennas at the BS and SCAs: NBS belongs to {20; 30; : : : ; 100}

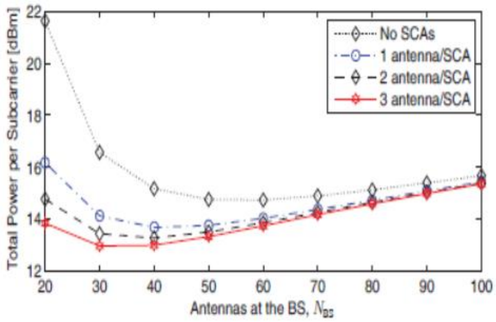

Fig. 4. Average total power consumption in the scenario different NBS and NSCA, while the QoS constraints are 2 bits/s/Hz.

Fig. 4 shows the average total power consumption (per subcarrier) in a scenario where the 10 users have QoS constraints of 2 bits/s/Hz. The optimal spatial multiflow transmission is obtained using Theorem 1.Fig. 4 demonstrates that adding more hardware can substantially decrease the total power consumption Pdynamic + Pstatic. This means that the decrease in the dynamic part, Pdynamic, due to better energy-focusing and less propagation losses clearly outweigh the increase in the static part, Pstatic, from the extra circuitry. Massive MIMO brings large energy efficiency improvements by itself, but the same power consumption can be achieved with half the number of BS antennas (or less) by deploying a few single-antenna SCAs in areas with active users. Further improvements in energy efficiency are achieved by having multi-antenna SCAs; a network topology that combines massive MIMO and small cells is desirable to achieve high energy efficiency with little additional hardware. However, there are saturation points where extra hardware will not decrease the total power anymore. Note that the power is shown in dBm, thus there are 10-fold improvements in Fig. 4.

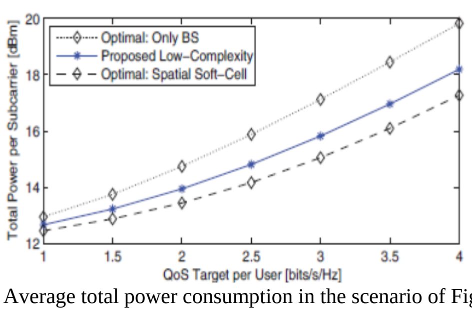

Fig. 5. Average total power consumption in the scenario of Fig. 3 with NBS = 50 and NSCA = 2. We consider different QoS constraints and beamforming

Although the system allows for multiflow transmission, the simulation shows only a 0–3% probability of serving a user by multiple transmitters. This is in line with Corollary 1. The main impact of increasing NSCA is that each SCA is likely to being allocated more than one user to serve exclusively; the probability is 20–45% for NSCA=3 but decreases with NBS. Next, Fig. 5 considers NBS = 50 and NSCA = 2 for different QoS constraints. Three beamforming algorithms are compared: 1) Optimal beamforming using only the BS; 2) Multiflow-RZF proposed in Section III-A; and 3) Optimal spatial soft-cell coordination from Theorem 1. As in the previous figure, we observe great improvements in energy efficiency by offloading users to the SCAs. The proposed Multiflow-RZF beamforming gives promising results for practical applications, because a majority of the energy efficiency improvements is achievable by judicious low-complexity beamforming techniques.

5. Conclusion

Wireless communications are undergoing a rapid evolution, wherein the quest for new services and applications pushes for the fast introduction of new technologies into the marketplace. Operators are just now starting to make initial profits from their deployed LTE networks, and already 5G demos and prototypes are being announced. Moreover, the wireless communications industry has begun to design for energy efficiency. The energy efficiency of cellular networks can be improved by employing massive MIMO at the BSs or overlaying current infrastructure by a layer of SCAs. This paper analyzed a combination of these concepts based on soft-cell coordination, where each user can be served by non-coherent beamforming from multiple transmitters. We proved that the power minimizing spatial multiflow transmission under QoS constraints is achieved by solving a convex optimization problem. The optimal solution dynamically assigns users to the optimal transmitters, which usually is only the BS or one of the SCAs. The analysis considered both the dynamic emitted power and static hardware consumption. We provide promising results showing that the total power consumption can be greatly improved by combining massive MIMO and small cells. Most of the benefits are also achievable by low-complexity beamforming, such as the proposed Multiflow-RZF beamforming.

6. Future scope

After having reviewed the state-of-the-art of the main 5G energy-efficient techniques, a natural question is: what are the next steps to be taken towards an energy efficient 5G? We review some of them in the following.

A. The need for a holistic approach

A holistic approach is thus necessary, in which all energy-efficient techniques are combined. Indeed, as previously discussed, some works in this special issue go in this direction combining multiple energy-efficient techniques together. The GreenTouch project [8], [9] has taken an initial end-to-end perspective for the assessment of the network energy efficiency and energy consumption. More research in this direction is needed to understand the relative impact and the combined benefits of new technologies, architectures and algorithms being developed.

B. Dealing with interference

Unfortunately, 5G networks will be interference-limited, since orthogonal transmission schemes and/or linear interference neutralization techniques are not practical due to the massive amount of nodes to be served. Thus, the potentialities of fractional programming must be extended. A promising answer is represented by the framework of sequential fractional programming, which provides a systematic approach to extend fractional programming to interference-limited networks with affordable complexity. Sequential fractional programming has been recently shown to be effective in optimizing the energy efficiency of a number of candidate technologies for 5G, such as C-RAN, CoMP, and multi-cell systems, also with multi-carrier transmissions [23], [47], multi-cell massive MIMO systems [47], heterogeneous relay-assisted interference networks [46], full-duplex systems [45], and device-to-device systems [64], [62].

C. Dealing with randomness

A second approach lies in the use of learning techniques, which deal with randomness by letting the devices learn from past observations of their surroundings and respond as appropriate in a self-organizing fashion. However, also in this case, very little research effort has been directed towards understanding the impact of this technique on energy-efficient network design.

D. Emerging techniques and new energy models

In addition, new emerging technologies can also be used for energy-efficient purposes. In particular, caching and mobile computing have shown significant potential as far as reducing energy consumption is concerned. By an intelligent distribution of frequently accessed content over the network nodes, caching alleviates the need for backhaul transmissions, which results in relevant energy consumption reductions. Instead, mobile computing does not directly reduce the energy consumption, but, similarly to wireless power transfer, it can prolong the lifetime of nodes that are low on battery energy. Nevertheless, in order to conclusively quantify the impact of these techniques on energy efficiency it is necessary to develop new energy consumption models which take into account the energy consumption associated with overhead transmissions over the backhaul, to feedback signaling, and to the execution of computing operations in digital signal processors.

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