IMPROVING ENERGY EFFICIENCY BY BAYESIAN CHANNEL ESTIMATION AND JOINT MULTIFLOW BEAMFORMING IN MASSIVE MIMO SYSTEM

A.Suban[1], G.Bhuvaneshwaran[2]

[1] Assistant Professor, Department of Electronics and Communication Engineering, Velammal College of Engineering and Technology, Viraganoor, Madurai, Tamil Nadu.

[2]PG final year student, Department of Electronics and Communication Engineering, Velammal College of Engineering and Technology, Viraganoor, Madurai, Tamil Nadu.

Abstract:To improve the cellular energy efficiency, without sacrificing quality-of-service (QoS) at the users, the network topology must be densified to enable higher spatial reuse. In this work a combination of two densification approaches, namely "massive" multiple-input multiple-output (MIMO) base stations and multiflowbeamforming technique are incorporated to improve the performance of the System. The fundamental limit on the performance of Massive -MIMO antenna systems is due to failure in accurate channel estimation. To address this problem, an estimation of channel parameters of the desired links in a target cell is proposed. It is shown that if the propagation properties of massive MIMO systems can be exploited, it is possible to obtain an accurate estimate of the channel parameters. The signals are observed in the beam domain (using Fourier transform), the channel is approximately sparse, i.e., the channel matrix contains only a small fraction of large components, and other components are close to zero. This observation then enables channel estimation based on sparse Bayesian learning methods, where sparse channel components can be reconstructed using a small number of observations. Results illustrate that compared to conventional estimators; the proposed approach achieves much better performance in terms of the channel estimation accuracy and achievable rates in the presence of pilot contamination. In addition to channel estimation, efficient energy power control technique for massive MIMO is adopted i.e., the total power consumption is minimized (both dynamic emitted power and static hardware power) while satisfying QoS constraints. This problem is proved to have a hidden convexity that enables efficient solution algorithms. Interestingly, the optimal solution promotes exclusive assignment of users to transmitters. Furthermore, promising simulation results showing how the total power consumption can be greatly improved by combining massive MIMO and joint multiflowbeamforming are provided..

Keywords : Massive MIMO, Joint Multiflow Beamforming, Convex Optimization.

I. Introduction

Wireless technology in a variety of forms is an area of electronics that is developing and growing particularly fast. As such, it has captured the attention of the media and the imagination of the public. In recent years, we are experiencing huge growth rates in wireless and mobile communication system. For many countries, wireless communication is the only solution due to the lack of an appropriate fixed communication infrastructure. All these make the wireless communication system so much popular and create ever-increasing demand to understand the development and possibilities of wireless communication. There are two fundamental aspects of wireless communication that make the problem challenging and interesting. First is the phenomenon of fading: the time variation of the channel strengths due to the small-scale effect of multipath fading, as well as large-scale effects such as path loss via distance attenuation and shadowing by obstacles. Second, unlike in the wired world where each transmitter–receiver pair can often be thought of as an isolated point-to-point link, wireless users communicate over the air and there is significant interference between them. Traditionally the design of wireless systems has focused on increasing the reliability of the transmission with less error. So the exploitation in the field of wireless communication is enormous. For the communication to take place reliably through longer distances there is a need for the information or the data to get modulated. And hence modulation plays a major role in the communication systems.Modulation is nothing but altering the characteristics of the carrier with respect to the information that is being processed.

MIMO (multiple inputs, multiple outputs) is an antenna technology for wireless communications in which multiple antennas are used at both the source (transmitter) and the destination (receiver). The antennas at each end of the communications circuit are combined to minimize errors and optimize data speed. MIMO (multiple-in, multiple-out) takes advantage of multiplexing to increase wireless bandwidth and range. MIMO algorithms send information out over two or more antennas and the information is received via multiple antennas as well. On normal radio, multiplexing would cause interference, but MIMO uses the additional pathways to transmit more information and then recombines the signal on the receiving end. MIMO systems provide a significant capacity gain over conventional single antenna systems, along with more reliable communication. The benefits of MIMO lead many to believe it is the most promising of emerging wireless technologies. Primary reason to use multiple antennas is to improve link quality and reliability

Massive MIMO makes a clean break with current practice through the use of a very large number of service antennas (e.g., hundreds or thousands) that are operated fully coherently and adaptively. Extra antennas help by focusing the transmission and reception of signal energy into ever-smaller regions of space. This brings huge improvements in throughput and energy efficiency, in particularly when combined with simultaneous scheduling of a large number of user terminals (e.g., tens or hundreds). Massive MIMO was originally envisioned for time division duplex (TDD) operation, but can potentially be applied also in frequency division duplex (FDD) operation. Other benefits of massive MIMO include the extensive use of inexpensive low-power components, reduced latency, simplification of the media access control (MAC) layer, and robustness to interference and intentional jamming. The anticipated throughput depends on the propagation environment providing asymptotically orthogonal channels to the terminals, and experiments have so far not disclosed any limitations in this regard. While massive MIMO renders many traditional research problems irrelevant, it uncovers entirely new problems that urgently need attention.

In this paper, we focus is on the channel estimation problems with pilot contamination in the uplink, although there are other related issues in the downlink that also greatly limit the performance of massive MIMO systems. For the issues in the downlink. Several approaches have emerged to deal with pilot contamination in the uplink recently. By exploiting the covariance information of user channels and applying a covariance-aware pilot assignment strategy among the cells, revealed that pilot contamination could disappear. Alternatively, using an eigenvalue decomposition of the sample covariance matrix of the received signals, claimed that pilot contamination can be effectively mitigated by projecting the received signal onto an interference-free subspace without the need of coordination amongst the cells. Nevertheless, rely heavily on the estimation of the channel or signal covariance matrices. Though the covariance matrices change slowly over time, the estimation problem under massive MIMO systems is far from trivial. The reason is that a covariance matrix is typically estimated through the sample covariance matrix, and that the sample size should be increased proportionally to the dimension of the covariance matrices.

In statistics and signal processing, a minimum mean square error (MMSE) estimator is an estimation method which minimizes the mean square error (MSE), which is a common measure of estimator quality, of the fitted values of a dependent variable. In the Bayesian setting, the term MMSE more specifically refers to estimation with quadratic loss function. In such case, the MMSE estimator is given by the posterior mean of the parameter to be estimated. Since the posterior mean is cumbersome to calculate, the form of the MMSE estimator is usually constrained to be within a certain class of functions. Linear MMSE estimators are a popular choice since they are easy to use, calculate, and very versatile. It has given rise to many popular estimators such as the Wiener–Kolmogorov filter and Kalman filter.

The term MMSE more specifically refers to estimation in a Bayesian setting with quadratic cost function. The basic idea behind the Bayesian approach to estimation stems from practical situations where we often have some prior information about the parameter to be estimated. For instance, we may have prior information about the range that the parameter can assume; or we may have an old estimate of the parameter that we want to modify when a new observation is made available; or the statistics of an actual random signal such as speech. This is in contrast to the non-Bayesian approach like minimum-variance unbiased estimator (MVUE) where absolutely nothing is assumed to be known about the parameter in advance and which does not account for such situations. In the Bayesian approach, such prior information is captured by the prior probability density function of the parameters; and based directly on Bayes theorem, it allows us to make better posterior estimates as more observations become available. Thus unlike non-Bayesian approach where parameters of interest are assumed to be deterministic, but unknown constants, the Bayesian estimator seeks to estimate a parameter that is itself a random variable. Furthermore, Bayesian estimation can also deal with situations where the sequence of observations is not necessarily independent. Thus Bayesian estimation provides yet another alternative to the MVUE. This is useful when the MVUE does not exist or cannot be found.

II. BAYESIAN CHANNEL ESTIMATION

Among various CS approaches, probabilistic Bayesian inference has recently attracted much attention for its outstanding recovery performance. In order to apply probabilistic Bayesian inference to, one requires to know distribution. To this end, the following two observations are useful. First, it can infer from that each element consists of a Gaussian random variable, although one should particularly notice that **h** and **H***b* in are observed from Different perspective. Second, we observe that the elements of **h** have significantly different variances, some of them are very small but some are large. Inspired by the two observations, we model the elements of **h** = [*hk, n*] by a Gaussian-mixture (GM) distribution.

AMP employs central limit theorem to *approximate* sum of many random variables as a Gaussian. To get an intuition on the algorithm, we provide an interpretation on each step. First of all, we view the target estimate *hk,n* as a Gaussian with mean *at k,n*and variance*vtk,n*at the*t*thiteration. Therefore, if we temporarily ignore thesecond term of , *ωt*+1*m,n* can be understood as a current mean estimate of the *m*th element of **Sh***n*, which has variance *V t*+1 *m,n* . Next, considering the conventional estimator by the matched filter, we get **S***h***y** where the approximation follows from the fact that **S***H***S**≈**I**.

AMP ITERATION

$$r^t = (Y - HS^{t-1}) + (n/m*\sigma^2/[\sigma^2 + \alpha^{t-1}]*r^{t-1})$$

Where,

$$\alpha^t = \sigma^2 + (n/m*[\alpha^{t-1}.\sigma^2]/\alpha^{t-1} + \sigma^2]$$

$$S^t = (\sigma^2/[\alpha^t + \sigma^2]) * (H*r^t + S^{t-1})$$

III. BEAMFORMING

Beamforming or spatial filtering is a signal processing technique used in sensor arrays for directional signal transmission or reception. This is achieved by combining elements in a phased array in such a way that signals at particular angles constructive experience interference while others experience destructive interference .Beamforming can be used at both the transmitting and receiving ends in order to achieve spatial selectivity. The improvement compared with Omni directional reception/transmission is known as the receive/transmit gain (or loss).

Beamforming can be used for radio or sound waves. It has found numerous applications in radar, sonar, seismology, wireless communication, radio astronomy, acoustic and biomedicine. Adaptive beamforming is used to detect and estimate the signal-of-interest at the output of the sensor array by means of optical (e.g. least-squares) spatial filtering and interference rejection. To change the directionality of the array when transmitting, a beamformer controls the phase and relative amplitude of the signal at each transmitter, in order to create a pattern of constructive and destructive interference in the wave front when receiving, information from different sensors is combined in a way where the expected pattern of radiation is preferentially observed.

$$\begin{aligned}
&\underset{\mathbf{w}_{k,j}\geq 0\,\forall_{k,j}}{\text{minimize}} \quad \sum_{j=0}^{S}\rho_j \sum_{k=1}^{K} t_r(\mathbf{w}_{k,j}) + P_{static} \\
&\textit{subject to} \quad rank(\mathbf{w}_{k,j}) \leq 1 \quad \forall_{k,j}, \\
&\qquad \sum_{j=0}^{S} h_{k,j}^{H}((1+\frac{1}{\gamma_k})\mathbf{w}_{k,j} - \sum_{i=1}^{K}\mathbf{w}_{i,j})h_{k,j} \geq \sigma_k^2 \ \forall_k, \quad \text{........(4.4.3.1)} \\
&\qquad \sum_{k=1}^{K} tr(q_{j,l}\mathbf{w}_{k,j}) \leq q_{j,l} \ \forall_{j,l},
\end{aligned}$$

ALGORITHM

This section derives algorithms for solving the optimization problem. The QoSconstraint 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 to spatial multiflow transmission. To achieve a convex reformulation, we use the notation Wk,j = wk,jwHk,j∀k,j. This matrix should bepositive semi-definite, denoted as Wk,j = 0, and haverank(Wk,j) ≤ 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 where the QoS targets have been transformed into SINR targets of ˜ γk = 2γk −1 ∀k. The problem (8) is convex except for the rank constraints, but we will now prove that these constraints can be relaxed without losing optimality.

1) It is only served by the BS $(i.e., \mathbf{w}_{k,j}^{*} = 0, 1 \leq j \leq S);$

2)It is only served by the jth SCA $(i.e., \mathbf{w}_{k,0}^{*} = 0 \ and \ \mathbf{w}_{k,i}^{*} = 0 \ for \ i \neq j);$

3) It is served by a combination of BS and SCAs, whereof at least one transmitter j has an active power constraint $(i.e., \sum_{k=1}^{K} tr(\mathbf{q}_{j,l}\mathbf{w}_{k,j}^{*}) = \mathbf{q}_{j,l})$

IV. CONVEX OPTIMIZATION

Convex programming studies the case when the objective function is convex (minimization) or concave (maximization) and the constraint set is convex. This can be viewed as a particular case of nonlinear programming or as generalization of linear or convex quadratic programming. Semidefinite programming (SDP) is a subfield of convex optimization where the underlying variables are semidefinite matrices. It is generalization of linear and convex quadratic programming.

V. PROBLEM FORMULATION

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.

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

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 hH k,0∈ C1×NBS and hHk,j∈C1×NSCA for the BS and jth 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 is

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

where x0,xj are the transmitted signals at the BS and jth SCA, respectively. The term nk∼CN(0,σ2 k) is the circularlysymmetric complex Gaussian receiver noise with zero-mean and variance σ2 k, measured in milliwatt (mW). The BS and SCAs are connected to a backhaul network that enables joint spatial soft-cell resource allocation but only linear non-coherent transmissions; that is, each user can be served by multiple transmitters but the information symbols will be coded and emitted independently. We call it spatial multiflow transmission [9] and it enables users barely covered by a SCA to receive extra signals from the BS or other SCAs. The information symbols from the BS and the jth SCA to user k are denoted xk,0 and xk,j, respectively, and originate from independent Gaussian codebooks with unit power (in mW); that is, xk,j∼ CN(0,1) for j = 0,...,S. These symbols are multiplied with the beamforming vectors wk,0∈ CNBS×1 and wk,j∈CNSCA×1 to obtain the transmitted signals

$$\mathbf{x}_j = \sum_{k=1}^{K} \mathbf{w}_{k,j}\mathbf{x}_{k,j},\ j = 0, \ldots\ldots, s$$

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 obtained automatically and optimally from the optimization problem solved herein. This paper considers minimization of the total power consumption while satisfying QoS constraints for each user. We will define both concepts before formulating the problem. The QoS constraints specify the information rate [bits/s/Hz] that each user should achieve in parallel. These are defined as, log2 (1 + SINRk) ≥ γk, where γk is the fixed QoS target and 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 phasesynchronization between transmitters, contrary to coherent jointtransmission that requires very tight synchronization [10]. The power consumption (per subcarrier) can be modeled as Pdynamic + Pstatic [5]–[7] with the dynamic and static terms

$$P_{dynamic} = \rho_0 \sum_{k=1}^{K} \left\| \mathbf{w}_{k,0} \right\|^2 + \sum_{j=1}^{S} \rho_j \sum_{k=1}^{K} \left\| \mathbf{w}_{k,j} \right\|^2$$

$$P_{static} = \frac{\eta_0}{C} N_{BS} + \sum_{j=1}^{S} \frac{\eta_j}{C} N_{SCA}$$

respectively. The dynamic term is the aggregation of the emitted powers,PK k=1kwk,jk2, each multiplied with a constantρ j ≥ 1 accounting for the inefficiency of the power amplifier at this transmitter. The static term, Pstatic, is proportional to the number of antennas and ηj ≥ 0 models the power dissipation in the circuits of each antenna (e.g., in filters, mixers, converters, and baseband processing). Pstatic is normalized with the total number of subcarriers C ≥ 1. Representative numbers on these parameters are given in Table I, [6], and [11] Each BS and SCA is prone to Lj power constraints

$$\sum_{k=1}^{K} \mathbf{w}_{k,j}^{H} q_{j,l} \mathbf{w}_{k,j} \le q_{j,l},\ l = 1, \ldots., L_j$$

The weighting matrices Q0∈CNBS×NBS,Qj,` ∈CNSCA×NSCA for j = 1,...,S, are positive semi-definite. The corresponding limits are qj,` ≥ 0. The parameters Qj,`,qj,` are fixed and can describe any combination of per-antenna, per-array, and softshaping constraints [10]. We typically have q0,`qj,` for 1 ≤ j ≤ S, because the BS provides coverage. Our numerical evaluation considers per-antenna constraints of qj [mW] at the jth transmitter, given by L0 = NBS, Lj = NSCA, qj,` = qj∀`, and Qj,` with one at `th 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, thus

$$\begin{aligned} &\underset{\mathbf{w}_{k,j}\forall_{k,j}}{\text{minimize}}\ P_{dynamic} + P_{static} \\ &\textit{subject to}\quad \log_2(1 + SINR_k) \ge \gamma_k \forall_k, \\ &\qquad\qquad \sum_{k=1}^{K} \mathbf{w}_{k,j}^{H} q_{j,l} \mathbf{w}_{k,j} \le q_{j,l} \forall_{j,l} \end{aligned}$$

$$\begin{aligned} &\underset{\mathbf{W}_{k,j}\ge 0\,\forall k,j}{\text{minimize}}\ \sum_{j=0}^{S} \rho_j \sum_{k=1}^{K} tr\left(\mathbf{W}_{k,j}\right) + P_{static} \\ &\textit{subjectto}\ rank\left(\mathbf{W}_{k,j}\right) \le 1\ \forall k, j, \\ &\sum_{j=0}^{S} \mathbf{h}_{k,j}^{H} \left(\left(1 + \frac{1}{\gamma_k} \right) \mathbf{W}_{k,j} - \sum_{i=1}^{K} \mathbf{W}_{i,j} \right) \mathbf{h}_{k,j} \ge \sigma_k^2\ \forall k, \\ &\sum_{k=1}^{K} tr\left(\mathbf{Q}_{j,l} \mathbf{W}_{k,j}\right) \le q_{j,l} \qquad \forall j, l \end{aligned}$$

wk,j∀k,j Pdynamic + Pstatic subject to log2 (1 + SINRk) ≥ γk∀k, K X k=1 wH k,jQj,`wk,j ≤ qj,` ∀j,`. (7) In the next section, we will prove that (7) can be reformulated as a convex optimization problem and thus is solvablein 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.

VI. RESULTS AND DISCUSSIONS

The measurement of performance of any communication depends on the calculation of the Bit Error Rate (BER). The bit error rate or bit error ratio is the number of bit errors divided by the total number of transferred bits during a studied time interval. In a noisy channel, the BER is often expressed as a function of the normalized signal-to-noise ratio measure denoted Eb/N0, (energy per bit to noise power spectral density ratio). Measuring the bit error ratio helps people choose the appropriate error correction codes. Transmitted data since the BER might be reduced, lowering the number of packets that had to be resent. The signal-to noise-ratio (SNR), Eb/N0, is from the SNR in decibels, 'snr in db', as: Eb/N0= 10^(snrdb/10)

usually expressed in decibels, but we must convert decibels to an ordinary ratio before we can make further use of the SNR. If we set the SNR to m dB, then Eb/N0 = 10m/10. Using Matlab, we find the ratio, 'Eb/N0',

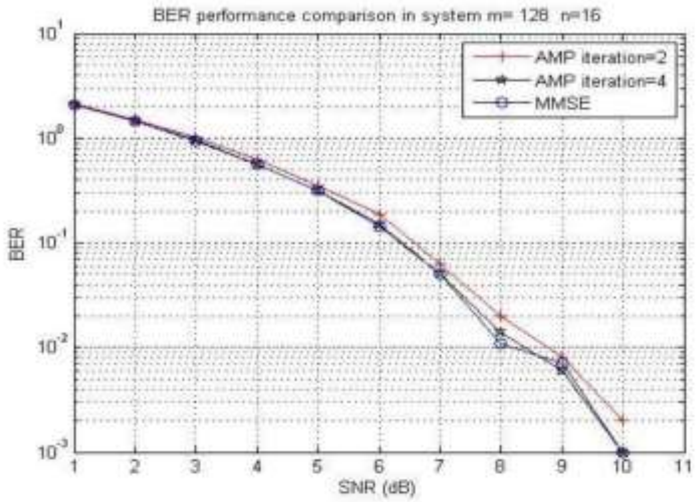

Fig.1 BER vs SNR for Various channel estimators

It is evident that by comparing AMP and MMSE we could get thesame result which gives the least possible error. AMP iteration 4 gives the same result as that of MMSE. Hence AMP 4 is the best suitable estimator

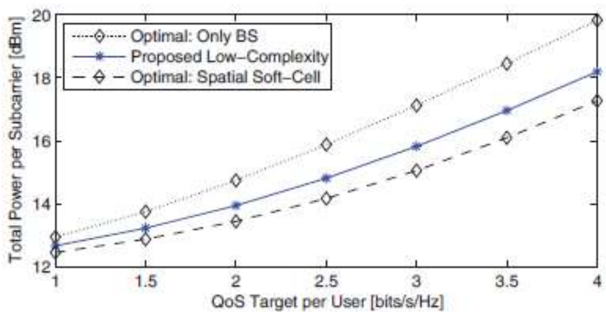

Fig.2 Average total power consumption

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 powerminimizing 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.

VII. REFERENCES

[1] F. Rusek, D. Persson, B. Lau, E. Larsson, T. Marzetta, O. Edfors, and F. Tufvesson, "Scaling up MIMO: Opportunities and challenges with very large arrays," IEEE Signal Process. Mag., vol. 30, no. 1, pp. 40– 60, 2013.

[2] J. Hoydis, S. ten Brink, and M. Debbah, “Massive MIMO in the UL/DL of cellular networks: How many antennas do we need?” IEEE J. Sel. Areas Commun., vol. 31, no. 2, pp. 160–171, 2013.

[3] S. Parkvall, E. Dahlman, G. J¨ongren, S. Landstr¨om, and L. Lindbom, “Heterogeneous network deployments in LTE – the soft-cell approach,” Ericsson Review, no. 2, 2011.

[4] J. Hoydis, M. Kobayashi, and M. Debbah, “Green small-cell networks,” IEEE Veh. Technol. Mag., vol. 6, no. 1, pp. 37–43, 2011.

[5] S. Cui, A. Goldsmith, and A. Bahai, “Energy-constrained modulation optimization,” IEEE Trans. Wireless Commun., vol. 4, no. 5, pp. 2349– 2360, 2005.

[6] G. Auer and et al., D2.3: Energy efficiency analysis of the reference systems, areas of improvements and target breakdown. INFSO-ICT-247733 EARTH, ver. 2.0, 2012.

[7] D. Ng, E. Lo, and R. Schober, “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.

[8] E. Bj¨ornson and E. Jorswieck, “Optimal resource allocation in coordinated multi-cell systems,” Foundations and Trends in Communications and Information Theory, vol. 9, no. 2-3, pp. 113–381, 2013.

[9] H. Holma and A. Toskala, LTE Advanced: 3GPP Solution for IMTAdvanced, 1st ed. Wiley, 2012.

[10] E. Bj¨ornson, N. Jald´en, M. Bengtsson, and B. Ottersten, “Optimality properties, distributed strategies, and measurement-based evaluation of coordinated multicell OFDMA transmission,” IEEE Trans. Signal Process., vol. 59, no. 12, pp. 6086–6101, 2011.

[11] R. Kumar and J. Gurugubelli, “How green the LTE technology can be?” in Proc. Wireless VITAE, 2011.

[12] M. Bengtsson and B. Ottersten, “Optimal and suboptimal transmit beamforming,” in Handbook of Antennas in Wireless Communications, L. C. Godara, Ed. CRC Press, 2001.

[13] S. Boyd and L. Vandenberghe, Convex Optimization. Cambridge University Press, 2004.

[14] J. Sturm, “Using SeDuMi 1.02, a MATLAB toolbox for optimization over symmetric cones,” Optimization Methods and Software, vol. 11-12, pp. 625–653, 1999.

[15] M. Bengtsson, “Jointly optimal downlink beamforming and base station assignment,” in Proc. IEEE ICASSP, 2001, pp. 2961–2964.

[16] Further advancements for E-UTRA physical layer aspects (Release 9). 3GPP TS 36.814, Mar. 2010.

[17] CVX Research Inc., “CVX: Matlab software for disciplined convex programming, version 2.0 beta,” http://cvxr.com/cvx, 2012.