ENERGY EFFICIENT DATA DETECTION FOR UPLINK MULTIUSER MASSIVE MIMO SYSTEMS

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Abstract

The massive multiuser multiple-input and multiple-output (MIMO) system is widely used in wireless communications considering their reliability and data speed. In multiuser MIMO uplink communications, it is necessary to design linear schemes that can be able to suppress co-channel interferences (CCIs). The optimal and suboptimal data detection algorithms like linear minimum mean square error (LMMSE), coordinate descent method (CDM), etc., may not provide satisfactory bit error rate (BER) performance. Here, we analyze the maximum ratio combining (MRC) receiver for a very large scale multiuser MIMO system under a composite-fading environment. It is developed in the context of an MRC receiver to analyze the mean square error (MSE) parameter with respect to the total training power. Thus with the help of MRC combined with CDM technique, the proposed system results better MSE performance or BER performance.

Keywords: LMMSE, Coordinate descent method, Maximum ratio combining receiver, Total training power, Massive MIMO

I. INTRODUCTION

Multiple-input multiple-output (MIMO) systems use multiple antennas at the transmitter and/or receiver to simultaneously transmit different data streams. Multiple antennas provide more degrees of freedom to the propagation channel and improve the throughput and link reliability. Such systems exploit the phenomenon of multipath propagation, which is traditionally a drawback in wireless communications, to the benefit of the user. The improvements in the performance offered by MIMO systems are due to diversity gain, spatial multiplexing gain, array gain and interference reduction. In massive MIMO systems, a large number of BS antennas improve spectral efficiency and radiated energy efficiency as compared to the existing wireless technologies.

A widely used suboptimal detection algorithm for uplink multiuser massive MIMO systems is the linear minimum mean square error (LMMSE) algorithm because of its favourable trade-off between bit error rate (BER) performance and complexity. However, the complexity of the LMMSE detector is still considerably high for large-scale MIMO systems.

Several reduced-complexity LMMSE-based detectors have been proposed for uplink massive multiuser MIMO systems to avoid exact large-scale MIMO matrix inversion. So there are various classical iterative algorithms like Richardson method (RM) which have further reduced the complexity of computing matrix inversion. To reduce the computational complexity of data detection, approximate message passing (AMP) and its variants, which were originally designed for compressed sensing, are applied to massive MIMO data detection. The AMP-based detector has the advantage of involving only matrix-vector multiplications rather than matrix-matrix multiplications. However, the AMP algorithm requires knowledge of noise variance and an inappropriate noise variance value would result in severe performance degradation. Moreover, when the MIMO channels are spatially correlated, the AMP-assisted detector may not converge, leadings to unacceptable performance.

The coordinate descent method (CDM), an old and simple technique that is surprisingly efficient and scalable, is now enjoying greatly renewed interest. Its revival is rooted in successful applications to big data optimization, machine learning, and other areas of interest.

As the number of antennas at the BS increases, linear receivers such as maximum ratio combining (MRC) and minimum mean squared error (MMSE) become optimal. With a large number of BS antennas, things that were random before now start to look deterministic. As a consequence, thermal noise and small-scale fading are averaged out in massive MIMO systems. In this paper, we analyze the maximum ratio combining (MRC) receiver for a very large scale multiuser MIMO system under a composite-fading environment. It is developed in the context of an MRC receiver to analyze the mean square error (MSE) parameter with respect to the total training power.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. Channel Model

We consider the uplink of a single cell multi-user massive MIMO system where a BS is equipped with M antennas. The BS receives the data from K single-antenna users in the same time-frequency resource. These transmissions are corrupted by the channel impairments. The transmissions from K users to the BS suffer from independent Rayleigh fading and lognormal shadowing. The M×1 received signal vector at the BS is given by

$$y = \sqrt{P_t} G x + n, \tag{1}$$

where G represents the M×K channel matrix between the K users and the M BS antennas, P_t is the average transmit power of a single user, x is the vector of symbols transmitted simultaneously by K users and n is the noise vector.

The channel matrix G models Rayleigh fading and lognormal shadowing. The channel coefficient g_{ik} between the ith BS antenna and the kth user can be represented as

$$g_{ik} = h_{ik}\sqrt{v_k} \tag{2}$$

where h_{ik} is the small-scale fading coefficient between the i_{th} BS antenna and the k_{th} user and v_k represents the large-scale fading of the k_{th} user such that $v_k \sim \log N\,(\mu_{(dB)}, \sigma^2_{(dB)})$. In a Rayleigh fading environment, the small-scale fading coefficient h_{ik} follows a complex normal distribution with zero mean and unit variance i.e., $h_{ik} \sim CN(0,1)$.

Since the BS antennas are closely spaced, the large-scale fading for a single user across M BS antennas is correlated. However, the small-scale fading coefficients are independent and identically distributed (i.i.d). In this thesis, we assume perfect correlation between the shadowing components of a single user across M BS antennas. Therefore, the received signals from the k_{th} user across M BS antennas suffer identical shadowing. The channel matrix G is then given by

$$G = HV^{1/2}, \tag{3}$$

where H is the M×K matrix of small-scale fading coefficients between the M BS antennas and K users and V is a K×K diagonal matrix containing the large-scale fading coefficients of K users. By using a linear detector, the received signal y is processed as

$$r = A^H y. \tag{4}$$

The vector r in (4) gives the received signals from all the users where A is the linear detector matrix that depends on the channel matrix G and H is the Hermitian operator.

B. SINR Formulation

After applying the linear detector and from (4), the received signal vector is given by

$$r = \sqrt{P_t} A^H G x + A^H n. \tag{5}$$

To formulate the SINR of a single user, the vector r is decomposed into two parts. Let r_j and x_j represent the received signal and the transmitted symbol of the j_{th} user, respectively. Then

$$r_j = \sqrt{P_t} a_j^H g_j x_j = \sqrt{P_t} \sum_{k=1,k\neq j}^{K} a_j^H g_k x_k + a_j^H n, \tag{6}$$

where a_j and g_j represent the j_{th} columns of the matrices A and G, respectively. The first term in (6) represents the desired signal of the j_{th} user, whereas the other two terms constitute interference from other users and noise, respectively. Without the loss of generality, we assume unit power spectral density of noise. The SINR of the j_{th} user can then be represented as

$$SINR_j = \frac{P_t \left|a_j^H g_j\right|^2}{P_t \sum_{k=1,k\neq j}^{K} \left|a_j^H g_k\right|^2 + \left\|a_j\right\|^2}. \tag{7}$$

III. RECEIVER DESIGN

In this section we design a linear receiver with the help maximum ratio combining (MRC) receiver combined with coordinate descent method (CDM) based algorithmic framework.

A. Maximum Ratio Combining Receiver

In case of perfect channel state information (CSI), the M × K linear detector matrix A for an MRC receiver is given by A = G hence, $a_j = g_j$. From (3) and (7), we obtain the SINR of a single user for an MRC receiver as

$$SINR_j^{mrc} = \frac{P_t \left\|h_j\right\|^4 v_j^2}{P_t v_j \sum_{k=1,k\neq j}^{K} \left|h_j^H h_k\right|^2 v_k + \left\|h_j\right\|^2 v_j}$$

$$\triangleq \frac{P_t \left\|h_j\right\|^2 v_j}{P_t \sum_{k=1,k\neq j}^{K} \frac{\left|h_j^H h_k\right|^2}{\left\|h_j\right\|^2} v_k + 1}. \quad (8)$$

Conditioned on h_j, we define a new RV g_k such that $g_k = \frac{\left|h_j^H h_k\right|}{\left\|h_j\right\|}$. g_k is a Gaussian RV with zero mean and unit variance that is independent of h_j. Therefore, $g_k \sim CN(0,1)$. From (8), the SINR is then given by

$$SINR_j^{mrc} = \frac{P_t \left\|h_j\right\|^2 v_j}{P_t \sum_{k=1,k\neq j}^{K} |g_k|^2 v_k + 1}. \quad (9)$$

Now we derive the probability density function (PDF) of the SNR. The numerator in (9) is the SNR, Z, of a single user at the BS. For notational simplicity, we omit the subscripts in the expression of Z. Therefore,

$$Z = P_t v \sum_{i=1}^{M} |h_i|^2 \coloneqq P_t v\, \gamma, \quad (10)$$

where $\gamma \sim \Gamma(M, 1)$ owing to the sum of independent and identically distributed exponential RVs each having a unit mean.
From (10), it is evident that the SNR follows a gamma-lognormal product distribution. The PDF of a gamma RV is given by

$$P_G(\gamma) = \frac{\gamma^{M-1} \exp(-\gamma)}{\Gamma(M)}, \quad (11)$$

where $\Gamma(\mathrm{M}) = (\mathrm{M}-1)!$ since M is an integer. The distribution of a product RV, Z=VG, is given by

$$P_Z(z) = \int_{-\infty}^{\infty} P_V(v) P_G\left(\frac{z}{v}\right) \frac{1}{|v|} dv. \quad (12)$$

Since, P_i is a constant, therefore, we neglect it in the PDF expression of gamma-lognormal product distribution. From (12), the PDF of the product of gamma and lognormal RVs is then given by

$$P_Z(z) = \frac{\xi z^{M-1}}{(M-1)!\,\sigma_{(dB)}\sqrt{2\pi}} \int_0^{\infty} \frac{exp(-z/v)}{v^{(M+1)}} exp\left(\frac{-(\xi \log_e v - \mu_{(dB)})^2}{2\sigma_{(dB)}^2}\right) dv, \quad (13)$$

From (13) it can be noticed that the PDF of SNR does not exist in a closed-form.

B. CDM-Based Signal Detector

The CDM optimizes one variable at a time while holding others fixed at their most recently updated values. Typically, the optimization coordinate is chosen cyclically. However, CDM is efficient when the subproblems can be solved quickly.
For a given $X_{-\mu} \triangleq [x_1, \dots, x_{\mu-1}, x_{\mu+1}, \dots, x_U]$, the optimal value of $x_\mu = A_\mu e^{j\theta_\mu}$ that minimizes $\|y - Hx\|^2$ is given by

$$A_\mu^\star = \frac{|\xi_\mu|}{\sum_{b=1}^{B} |H_{b\mu}|^2} \tag{14a}$$

$$\theta_\mu^\star = \arg\{\xi_\mu\}, \tag{14b}$$

Where

$$\xi_\mu \triangleq \sum_{b=1}^{B} H_{b\mu}^\star \left(y_b - \sum_{v=1, v\neq\mu}^{U} H_{bv} A_v e^{j\theta_v}\right). \tag{15}$$

To outline the problem concretely the optimal update problem can be written as

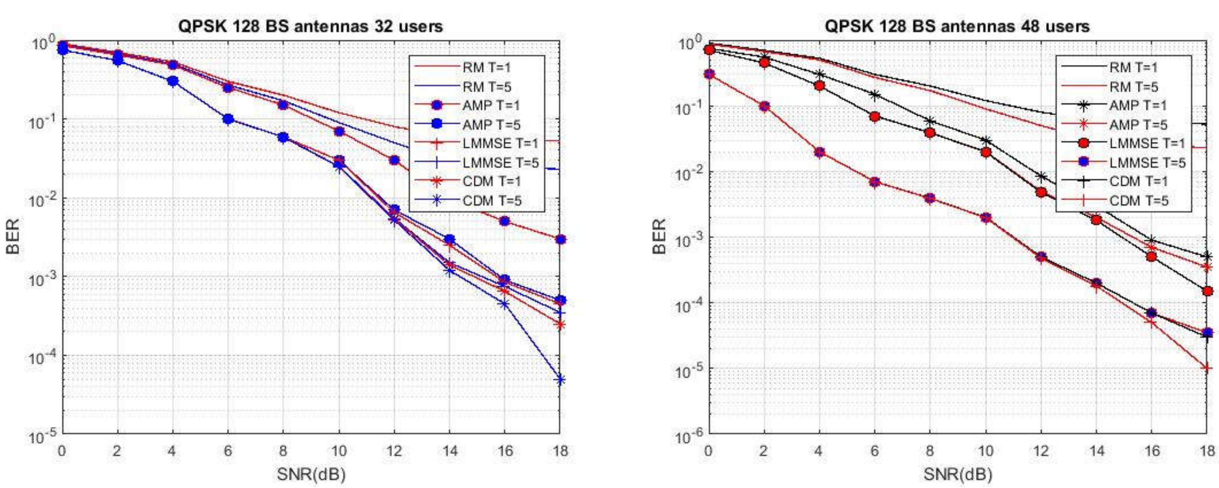
$$A_\mu^\star e^{j\theta_\mu^\star} = \arg\min \|y - Hx\|^2 \tag{16}$$

$$= \arg\min \sum_{b=1}^{B} \left|y_b - \sum_{v=1}^{U} H_{bv} A_v e^{j\theta_v}\right|^2. \tag{17}$$

IV. SIMULATION RESULTS AND DISCUSSION

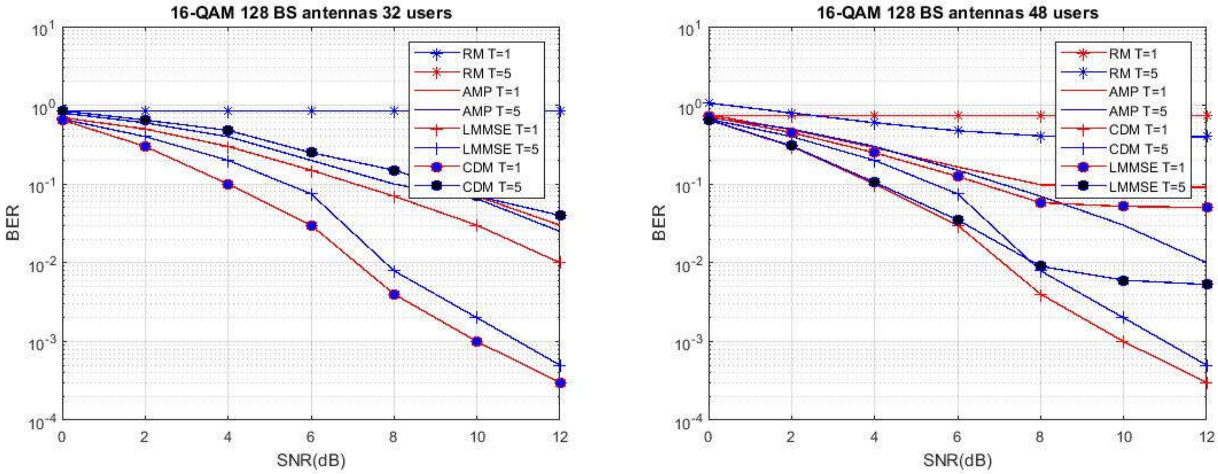
In this section, the BER and complexity performance of the proposed CDM-based detector are evaluated through Monte Carlo simulations, where each entry of the channel matrix H is an independent circularly symmetric complex Gaussian random variable (i.e., $H_{b\mu} \sim \mathcal{N}_{\mathbb{C}}(0, 1/B)$). The signal-to-noise ratio (SNR) is given by E_b/N_0, where E_b is the bit energy. For comparison, other approximate data detection methods for massive multiuser MIMO systems were also tested, including the RM-based detector [4], the AMP-based detector [8], and the classical LMMSE detector.

Figs. 1(a) and 1(b) illustrate the BER results as a function of SNR using QPSK modulation for antenna configuration $B\times U$ = 128×32 and $B\times U$ = 128×48. Here we consider two types of time durations or slots, say T=1 and T=5 for all the four techniques RM, AMP, LMMSE and CDM. These figures provide the following observations: First, for a fixed B, increasing U deteriorates the BER performance for these algorithms under the same SNR value. Second, the BER performance improves as the number of iterations increases for the RM assisted detector, the AMP-assisted detector, and the proposed CDM-based detector. When the iteration counts are the same, excluding the initial two iterations, the BER performance of the proposed CDM-based detector is superior to that of the RM-assisted detector and the AMP-assisted detector regardless of the antenna configuration employed. Thus, the proposed CDM-based detector requires less iteration to achieve the same BER performance as the RM-assisted detector and the AMP-assisted detector.



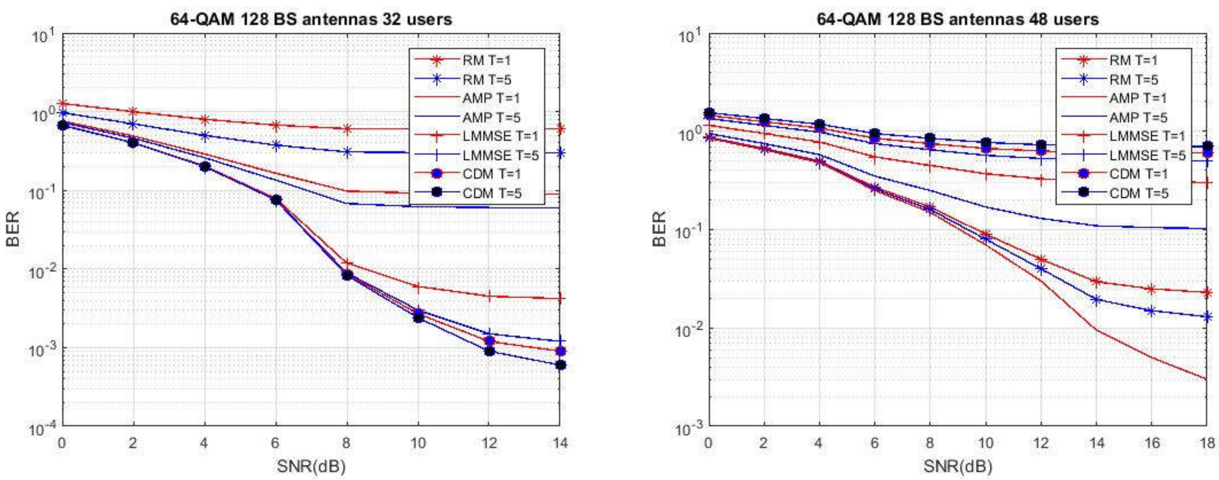
(a) 128 BS antennas and 32 users (b) 128 BS antennas and 48 users

Fig. 1. BER versus SNR for (a) the 128 × 32 massive MIMO system with QPSK modulation and (b) the 128 × 48 massive MIMO system with QPSK modulation.



(a) 128 BS antennas and 32 users (b) 128 BS antennas and 48 users

Fig. 2. BER versus SNR for (a) the 128 × 32 massive MIMO system with 16-QAM modulation and (b) the 128 × 48 massive MIMO system with 16-QAM modulation.



(a) 128 BS antennas and 32 users (b) 128 BS antennas and 48 users

Fig. 3. BER versus SNR for (a) the 128 × 32 massive MIMO system with 64-QAM modulation and (b) the 128 × 48 massive MIMO system with 64-QAM modulation.

Next, we examined the behaviour of the proposed CDM based detector for higher-order and non-constant amplitude modulations. Figs. 2 and 3 shows the BER displayed as a function of SNR for different antenna configurations with 16-QAM and 64-QAM modulation, respectively. The settings were identical to those in Fig. 1 except for the modulation scheme. Figs. 2 and 3 reveal similar performance trends to those exhibited in Fig. 1, which implies that most of the observations of Fig. 1 also hold true for these scenarios with 16-QAM and 64-QAM modulation schemes. However, because of the increase in the order of the modulation (the size of the problem), the RM-assisted detector, the AMP-assisted detector, and the proposed CDM-based detector require more iterations to obtain the desired results than do those in Fig. 1 under the same antenna configuration (Figs. 2 and 3).

We examine in below Fig. 4 the impact of noice variance for the CDM based detector having antenna configuration $B \times U = 128 \times 32$ massive MIMO system without spatial correlation using 16-QAM modulation. We can see that the BER performance of the CDM based detector is not affected by an inappropriate σ_ω^2 compared to the other data detection techniques.

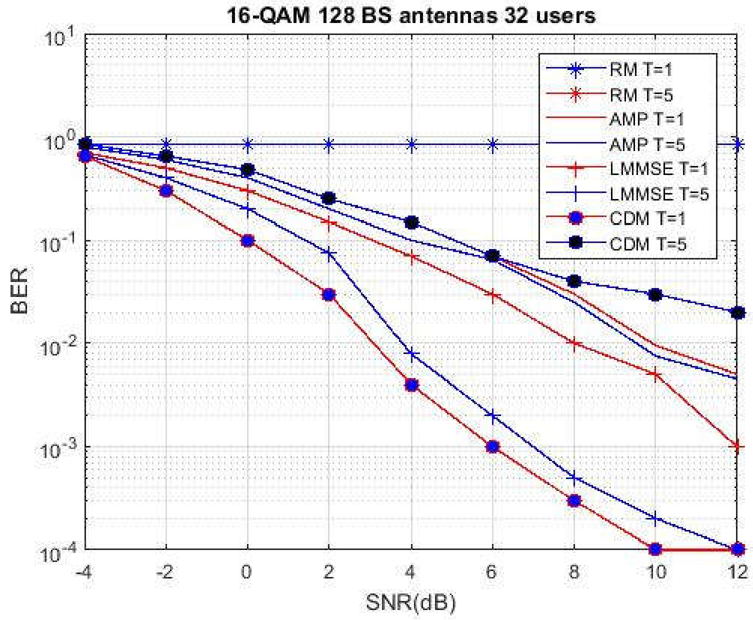


Fig. 4. BER versus SNR for the 128 × 32 massive MIMO system with 16-QAM modulation, where the RM, AMP, LMMSE and CDM assisted detectors, adopts inappropriate σ_ω^2 drawn from a uniform distribution on the interval from $\mathcal{U}_a$ to $\mathcal{U}_b$.

Finally from the below Fig. 5 we can observe the Total Training Power with respect to Mean Square Error behaviour for different data detection methods. We can clearly analyze in the context of an MRC receiver the MSE parameter with respect to the total training power.

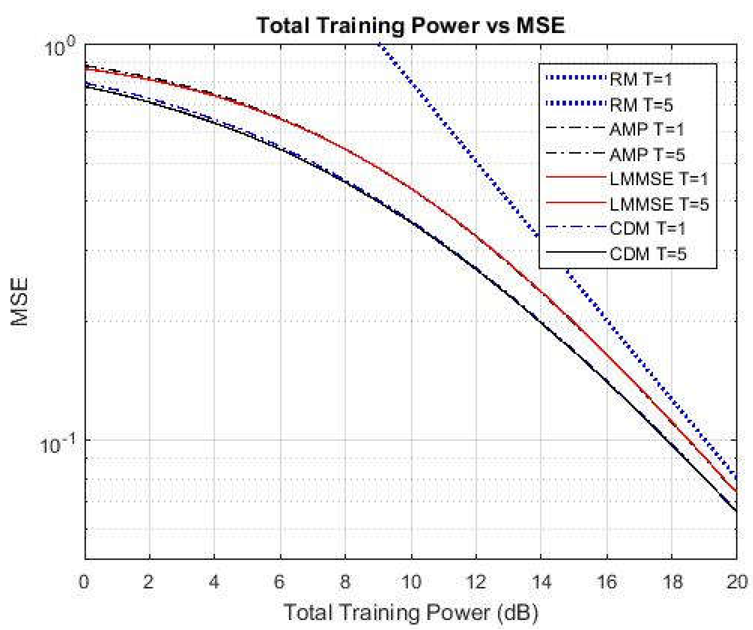


Fig. 5. Total Training Power versus MSE for massive MIMO system in comparison of different methods RM, AMP, LMMSE and CDM.

So with the help of MRC combined with CDM technique, the proposed system results better MSE performance compared to the remaining methods. This shows the effectiveness and efficiency of the proposed method.

V. CONCLUSION:

In this paper, we have proposed an energy efficient and low complexity data detection method for uplink multiuser massive MIMO systems. The optimal and suboptimal data detection algorithms like linear minimum mean square error, approximate message passing, etc., may not provide satisfactory bit error rate (BER) performance. Here, we considered a maximum ratio combining (MRC) receiver for a very large scale multiuser MIMO system under a composite-fading environment and combined it with the coordinate descent method (CDM) technique. We have taken CDM into consideration because of its low complexity and better performance compared to other conventional techniques. The simulation results show that the proposed system results better MSE or BER performance. The comparison results analyzing total training power with respect to MSE for the different methods RM, AMP, LMMSE and CDM shows the energy efficiency of the proposed system Thus this new approach is substantially energy efficient and low complex.

REFERENCES

[1] Jung-Chieh Chen, “A low complexity data detection algorithm for uplink multiuser massive MIMO systems,” IEEE journal on selected areas in communications, vol. 35, no. 8, Aug. 2017.

[2] Muhammad Saad Zia and Syed Ali Hassan, “On the Impacts of Composite Fading on Large-Scale Multi-User MIMO Systems,” IEEE Communications Letters, vol. 19, no. 12, Dec. 2015.

[3] E. G. Larsson, O. Edfors, F. Tufvesson, and T. L. Marzetta, “Massive MIMO for next generation wireless systems,” *IEEE Commun. Mag.*, vol. 52, no. 2, pp. 186–195, Feb. 2014.

[4] X. Gao, L. Dai, Y. Ma, and Z. Wang, “Low-complexity near-optimal signal detection for uplink large-scale MIMO systems,” *Electron. Lett.*, vol. 50, no. 18, pp. 1326–1328, Aug. 2014.

[5] H. Q. Ngo, E. G. Larsson, T. L. Marzetta, “Energy and spectral efficiency of very large multiuser MIMO systems," IEEE Trans. Wireless Commun., vol. 61, no. 4, pp. 1436-1449, April 2013.

[6] S. Wu, L. Kuang, Z. Ni, J. Lu, D. D. Huang, and Q. Guo, “Low complexity iterative detection for large-scale multiuser MIMO-OFDM systems using approximate message passing,” *IEEE J. Sel. Topics Signal Process.*, vol. 8, no. 5, pp. 902–915, Oct. 2014.

[7] S. J. Wright, “Coordinate descent algorithms,” *Math. Program*, vol. 151, no. 1, pp. 3–34, Jun. 2015.

[8] M. Bayati and A. Montanari, “The dynamics of message passing on dense graphs, with applications to compressed sensing,” *IEEE Trans. Inf. Theory*, vol. 57, no. 2, pp. 764–785, Feb. 2011.

[9] K. Li, X. Song, M. O. Ahmad, and M. N. S. Swamy, “An improved multicell MMSE channel estimation in a massive MIMO system," Int. J.Antennas Propag., 2014, doi:10.1155/2014/387436.

[10] N. Kim, Y. Lee and H. Park, “Performance analysis of MIMO system with linear MMSE receiver," IEEE Trans. Wireless Commun., vol. 7, no.11, pp. 4474-4478, 2008.

[11] A. Kammoun, M. Kharouf, W. Hachem and J. Najim, “BER and outage probability approximations for LMMSE detectors on correlated MIMO channels," IEEE Trans. Inf. Theory, vol. 55, no. 10, pp. 4386-4397, 2009.