Multiple-input multiple-output (MIMO) systems greatly increase the overall throughput of wireless systems since they are capable of transmitting multiple streams employing the same time-frequency resources. However, this gain requires an appropriate precoder design and a power allocation technique. In general, precoders and power allocation schemes are designed assuming perfect channel state information (CSI). Nonetheless, this is an optimistic assumption since real systems only possess partial or imperfect CSI at the transmitter (CSIT). The imperfect CSIT originates residual inter-user interference, which is detrimental for wireless systems. In this paper, two adaptive power allocation algorithms are proposed, which are more robust against CSIT imperfections than conventional techniques. Both techniques employ the mean square error as the objective function. Simulation results show that the proposed techniques obtain a higher performance in terms of sum-rate than conventional approaches.

Index Terms— Multiuser MIMO systems, power allocation, adaptive techniques, robust algorithms.

1. INTRODUCTION

Modern wireless communications systems rely on architectures where both the transmitter and the receiver are equipped with multiple antennas, also known as multiple-input multiple-output (MIMO) systems [1] [2] [3]. The main advantage of MIMO systems is that they increase dramatically the overall throughput without the need for additional bandwidth [4]. This gain comes from the simultaneous transmission of multiple data streams which share the same time-frequency resources.

An efficient transmission over the downlink (DL) of a MIMO system depends on the appropriate design and implementation of precoding and power allocation schemes [5] [6] [7] [8] [9] [10] [11] [12] [13] [14] [15] [16] [17] [18] [19] [20] [21] [22] [23] [24] [25]. Precoding allows the decoding of the information at the receiver by exploiting the multi-path propagation and suppressing the multiuser interference (MUI) [26] [27] [28] [29] [30] [31] [32] [33] [34] [35] [36] [37] [38] [39] [40] [41] [42] [43] [44] [45] [46] [47]. In addition, the achievable data rate associated with the users is affected by the power allocation scheme adopted, which must allocate the power levels according to the channel conditions.

The power allocation problem becomes non-convex in a multi-user MIMO (MU-MIMO) scenario due to the MUI, which requires an exhaustive search over the entire space of possible values to find the optimal. Indeed, the power allocation problem is an NP-hard problem [48] [49] and finding the optimal solution is computational demanding. In [50] [51] [52] the optimal power allocation is found through monotonic optimization at the expense of an exponential growing in computational complexity. In [53], a scenario where the users are equipped with single-antenna terminals is analyzed. In [54] [55], the previous work is extended to a MU-MIMO scenario where devices with multiple antennas are considered. Both approaches require the formulation and solution of geometric programming (GP) which is computational demanding. The connection between SINR and weighted sum rate (WSR) has been explored in [56]. In [57], the receiver and the power allocation parameters of a multihop wireless sensor network are found through alternating optimization. Due to the complexity of the previous approaches, in [58] local optimal solutions have been studied, reducing the complexity. Practical power allocation algorithms based on water-filling are presented in [59], whereas algorithms based on the weighted minimum mean square error (WMMSE) minimization are reported in [60] and fractional programming (FP) [61] are present in [62]. In [63], power allocation techniques based on convex optimization and adaptive processing were proposed for cell-free MIMO systems to maximize the minimum rate achieved among users.

In general, precoding and power allocation are performed assuming perfect knowledge of the channel state information at the transmitter (CSIT). Under this assumption the optimal power for diverse performance metrics (such as BER, sum-rate and fairness) is usually known [64] and closed form expressions for specific setups are available, such as for zero-forcing precoders [65]. However, time division duplex (TDD) systems employ training pilots to acquire CSIT whereas frequency division duplex (FDD) systems depend on feedback links. Both methods introduce error in the estimation procedure, which leads to an imperfect CSIT estimate [66]. Thus, real world systems do not meet the perfect CSIT assumption. The imperfect CSIT originates residual MUI which is detrimental to the system performance. Robust precoding techniques based on the worst-case performance optimization have been proposed to deal with the uncertainties [67] [68]. Later, the precoder design incorporates subspace projection techniques to increase the robustness against CSI imperfections [69]. Since CSIT imperfections degrade heavily the overall system performance, the design of robust techniques is of great importance.

In this paper, two adaptive power allocation techniques are developed, namely the mean square error adaptive power allocation (M-APA) and the robust M-APA (RM-APA). These techniques minimize the mean square error (MSE) between the information at the transmitter and the received signal. The main difference between these techniques is that the RM-APA employs statistical information of the CSIT error. The performance achieved is compared with the uniform power allocation (UPA) and the optimal power allocation.
Simulation results show that the APA algorithms attain a better performance in terms of sum-rate than UPA and comparable to optimal power allocation.

The rest of this paper is organized as follows. In Section 2 the system model is presented. The M-APA and RM-APA algorithms are derived and detailed in Section 3. Section 4 shows the simulation results, where the sum-rate of the proposed and conventional techniques are depicted. Finally, Section 5 draws the conclusions of this work.

2. SYSTEM MODEL

Let us consider the DL of a MU-MIMO system where the BS, which is equipped with $N_t$ antennas, transmits data to $K$ users. The $k$th user is equipped with $N_k$ antennas. Therefore, the total number of receive antennas is given by $N_r = \sum_{k=1}^{K} N_k$. The messages are encoded and modulated into a vector of symbols $s^T \in \mathbb{C}^{N_r}$. A power allocation matrix $P \in \mathbb{R}^{N_t \times N_r}$ contains the weights that allocates the power to the symbols. Once the power is allocated, a precoder $P \in \mathbb{C}^{N_t \times N_r}$ maps the symbols to the transmit antennas. Then, the transmitted vector $x \in \mathbb{C}^{N_t}$ can be expressed as follows:

$$x = P \mathbf{a} = P \mathbf{d}(a) s$$

$$= \sum_{m=1}^{N_r} a_m s_m \mathbf{p}_m. \quad (1)$$

The system has a transmit power constraint given by $E \left[|x|^2\right] \leq E_{tr}$, where $E_{tr}$ denotes the total available power.

Once the information is ready for transmission it is sent to the receivers through a channel $H = \tilde{H} + \bar{H} \in \mathbb{C}^{N_r \times N_t}$. The matrix $\tilde{H}$ represents the channel estimate and the matrix $\bar{H}$ models the CSIT imperfection by adding the error of the estimation procedure. Each coefficient $h_{ij}$ of the matrix $H$ represents the link between the $i$th receive antenna and the $j$th transmit antenna. The channel matrix can be expressed by $H = [H_1, H_2, \ldots, H_K]$, where $H_k$ denotes the channel connecting the BS to the $k$th user.

The received signal obtained following the model established is

$$y = Hx + n,$$  

$$E \left[|y|^2\right] \leq E_{tr}, \quad (2)$$

where $n \in \mathbb{C}^{N_r \times 1}$ is the additive noise modelled as a circularly symmetric complex Gaussian random vector, i.e., $n \sim \mathcal{CN}(0, \mathbf{R}_n)$.

3. ADAPTIVE POWER ALLOCATION

Let us consider the MU-MIMO model described in the previous section. Assuming knowledge of the precoder which remains fixed during the transmission of a packet, the problem is to find suitable values for the coefficients $a_i$ for $i = 1, 2, \ldots, N_r$ to enhance the overall performance of the system. For this purpose let us consider the minimum mean square error (MMSE) between the transmitted signal and the estimated signal at the receiver as the objective function given by

$$\min_a \mathbb{E} [\varepsilon]$$

s.t. $\text{tr} (P \mathbf{d}(a) P^H) = \frac{E_{tr}}{\sigma_n^2}, \quad (3)$

where the error is defined as $\varepsilon = \|s - y\|^2$ and the transmit power constraint is $\frac{E_{tr}}{\sigma_n}$. Evaluating the error, we get

$$\varepsilon = \|s - HP \mathbf{d}(a) s - n\|^2$$

$$= s^H \mathbf{d}(a) P^H H^H HP \mathbf{d}(a) s - s^H HP \mathbf{d}(a) s$$

$$+ s^H s + n^H HP \mathbf{d}(a) s - n^H s - s^H n + n^H n. \quad (4)$$

Remark that equation (4) is a scalar. Thus we can apply the trace operator over the right-hand side of the equation while preserving the equality. By applying the property $\text{tr} (C + D) = \text{tr} (C) + \text{tr} (D)$, where $C$ and $D$ are two general matrices with the same dimension, we obtain

$$\varepsilon = \text{tr} (s^H s) + \text{tr} (s^H \mathbf{d}(a) P^H H^H HP \mathbf{d}(a) s)$$

$$- \text{tr} (s^H HP \mathbf{d}(a) s) - s^H \mathbf{d}(a) P^H H^H s$$

$$- \text{tr} (n^H s) + \text{tr} (s^H n) + \text{tr} (s^H \mathbf{d}(a) P^H H^H n)$$

$$+ \text{tr} (n^H HP \mathbf{d}(a) s) + \text{tr} (n^H n). \quad (5)$$

Taking the expected value of (5) leads us to

$$E [\varepsilon] = \text{tr} (\mathbf{d}(a) P^H H^H HP \mathbf{d}(a) \mathbf{R}_a)$$

$$- \text{tr} (\mathbf{R}_a) \text{tr} (\mathbf{d}(a) P^H H^H)$$

$$+ \text{tr} (\mathbf{R}_a) \text{tr} (\mathbf{d}(a) P^H H^H), \quad (6)$$

where the elements of the input vector are assumed uncorrelated with zero mean and unit variance. By taking the derivative of (6) with respect to power loading matrix $\mathbf{A}$ and using the equality $\frac{\partial \text{tr} \mathbf{CD}}{\partial \mathbf{C}} = \mathbf{D} \circ \mathbf{I}$, where $\mathbf{C}$ is a diagonal matrix, we obtain

$$\frac{\partial E [\varepsilon]}{\partial \mathbf{A}} = 2 \left( P^H H^H HP \mathbf{d}(a) \right) \circ \mathbf{I}$$

$$- \left( P^H H^H \right) \circ \mathbf{I} - (HP) \circ \mathbf{I},$$

$$= 2 \left( P^H H^H HP \mathbf{d}(a) \right) \circ \mathbf{I} - 2 \Re \{(HP) \circ \mathbf{I}\}. \quad (7)$$

Employing a stochastic gradient descent approach we obtain the following update equation:

$$a [i] = a [i - 1] - \mu \frac{\partial E [\varepsilon]}{\partial \mathbf{A}}$$

$$= a [i - 1] - \mu \left( P^H H^H HP \mathbf{d}(a [i - 1]) \right) \circ \mathbf{I}$$

$$- \mu \Re \{(HP) \circ \mathbf{I}\}, \quad (8)$$

where $\mu$ is the step size that governs the learning rate of the adaptive algorithm. The precoders in the previous equation are assumed to have columns with unitary norm. Moreover, the vector $a$ is normalized before running the adaptive algorithm in order to have unitary norm. Therefore, the transmit power constraint is $\text{tr} (\mathbf{d}(a) \circ \mathbf{a}) = 1$. After each iteration the coefficients are properly scaled employing a power scaling factor $\beta$ to satisfy the transmit power constraint. Fig. 1 shows the curves of (3) for three different linear precoders where only two streams are being transmitted. In all cases the function is convex. Algorithm 1 summarizes the proposed adaptive power allocation strategy.
4. ROBUST ADAPTIVE POWER ALLOCATION

Let us now derive the RM-APA algorithm, which takes into account the statistical knowledge of the CSIT imperfections. First, consider the square of the error function given by

$$\varepsilon = \| s_p - \hat{H} \text{diag}(a) s_p - \hat{H} \text{diag}(a) s_p - n \|^2. \quad (9)$$

By expanding the terms, we have

$$\varepsilon = s^H \text{diag}(a) P^H \hat{H} \text{diag}(a) s - 2 \Re \left( s^H \hat{H} \text{diag}(a) n \right) + n^H n - 2 \Re \left( s^H \hat{H} \text{diag}(a) s \right) - 2 \Re \left( s^H n \right) + s^H \text{diag}(a) P^H \hat{H} \text{diag}(a) s + s^H s + 2 \Re \left( s^H \text{diag}(a) P^H \hat{H} \text{diag}(a) s \right) + 2 \Re \left( s^H \text{diag}(a) \hat{H} \text{diag}(a) s \right) + 2 \Re \left( s^H \text{diag}(a) \hat{H} \text{diag}(a) s \right) + 2 \Re \left( s^H n \right). \quad (10)$$

Including the trace operator over the right-hand side and taking the expected value we obtain

$$\mathbb{E}_{\varepsilon | H} = \text{tr} (R_a) - 2 \text{tr} \left( \Re \left( \hat{H} \text{diag}(a) R_a \right) \right) + \text{tr} \left( \Re \left( \text{diag}(a) P^H \hat{H} \text{diag}(a) R_a \right) \right) + \text{tr} \left( \Re \left( \text{diag}(a) P^H \hat{H} \text{diag}(a) R_a \right) \right) + \text{tr} \left( \text{diag}(a) P^H \hat{H} \text{diag}(a) R_a \right) \cdot \quad (11)$$

Note that the system has only access to $\hat{H}$. Moreover, the entries of $\hat{H}$ have a variance equal to $\sigma^2_j$, zero mean and are independent from the elements in $H$. By taking the expected value with respect to $\hat{H}$ to average out the effects of the channel uncertainties, we arrive at

$$\mathbb{E}_{\hat{H}} = \text{tr} (R_a) - 2 \text{tr} \left( \Re \left( \hat{H} \text{diag}(a) R_a \right) \right) + \text{tr} \left( \text{diag}(a) P^H \hat{H} \text{diag}(a) R_a \right) \cdot \quad (12)$$

where we consider that $\hat{h}_k$ is a random vector independent from $\hat{h}_j$ with $j \neq k$. Furthermore, the diagonal error matrix $\Xi$ is defined by

$$\Xi = \mathbb{E} \left[ \hat{H}^H \hat{H} \right] = \begin{bmatrix} \sigma^2_e & 0 & \cdots & 0 \\ 0 & \sigma^2_e & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma^2_e \end{bmatrix}. \quad (13)$$

Without loss of generality, we consider that $\sigma^2_e = \sigma^2_j$ $\forall i, j$. Furthermore, $\sigma^2_i = N_e \sigma_e$, which leads us to

$$\Xi = N_e \begin{bmatrix} \sigma^2_e & 0 & \cdots & 0 \\ 0 & \sigma^2_e & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma^2_e \end{bmatrix}. \quad (14)$$

By taking the derivative of $\frac{\partial \mathbb{E}_{\hat{H}}}{\partial H_a} \frac{\varepsilon | H}{A}$ with respect to $A$, we obtain

$$\frac{\partial \mathbb{E}_{\hat{H}}}{\partial H_a} \frac{\varepsilon | H}{A} = 2 \left( P^H \hat{H} \text{diag}(a) \circ I - 2 \Re \left( \hat{H} \text{diag}(a) \circ I \right) + 2 \left( P^H \Xi \text{diag}(a) \circ I \right) \cdot \quad (15)$$

From (15) we devise a gradient descent recursion, which is given by

$$a[i] = a[i - 1] + \mu \left( \hat{H} \text{diag}(a) \circ I \right) - \mu \left( P^H \hat{H} \text{diag}(a) \circ I \right) \cdot \quad (16)$$

The statistical information of the CSIT imperfection is included into the recursion of the power allocation coefficients, increasing the robustness against CSIT uncertainties. The proposed technique aims at maximizing the average sum-rate given a channel estimate $\hat{H}$, since the instantaneous rate is not achievable.

5. SIMULATIONS

In this section, the performance of the proposed power allocation techniques is assessed against conventional approaches. We consider a MU-MIMO system where the BS is equipped with four antennas and transmits data to two users, each equipped with two antennas. The inputs are statistically independent and follow a Gaussian distribution. A flat fading Rayleigh channel, which remains fixed during the transmission of a packet, is considered. Moreover, we assume additive white Gaussian noise with zero mean and unit variance. It follows that the SNR varies with $E_{\text{SNR}}$.

First, let us analyse the learning curves of the adaptive algorithms. Fig. 3 shows the mean square deviation (MSD) obtained with...
three different linear precoders, namely the matched filter (MF), the zero-forcing (ZF) and the MMSE precoders \cite{68}. To compute the MSD, we employ the optimum value that solves (3). This value was obtained through exhaustive search with a step of 0.005. The learning curves were obtained by averaging over 1000 independent Monte Carlo simulations. The step of the adaptive algorithm was set to 0.01 for all precoders. The adaptive algorithm reaches its steady state with about 30 iterations, which corresponds to a fast convergence.

In the next experiment, we consider an imperfect CSIT scenario with $\sigma_e^2 = 0.1$. The ergodic sum-rate was obtained by averaging 10000 independent channels. Fig. 3 shows the performance obtained employing different power allocation techniques with ZF and MMSE precoders. As expected, the best performance is attained with the exhaustive search, i.e., ES. However, the very high computational complexity of the ES approach makes it impractical. Moreover, the time spent increases exponentially with the number of users. The proposed strategies not only increase the performance of the system when compared to UPA but also have low computational complexity, which is very important for real communication systems. We can notice that the robust RM-APA approach performs better than the M-APA algorithm at the expense of a slight increase in computational complexity, which is justified based on the improved performance of RM-APA over M-APA. In addition, the proposed M-APA and RM-APA algorithms significantly outperform the uniform power allocation, i.e., UPA, and the random power allocation, denoted as Random, strategies.

6. CONCLUSION

In this paper, the M-APA and RM-APA adaptive power allocation algorithms were developed and shown to obtain better performance than the conventional UPA under imperfect CSIT. Recursive expressions to update the power allocation parameters were derived, which keep linear complexity since only simple multiplications and additions are required. RM-APA employs statistical information from the error, attaining the best performance among the proposed algorithms.

7. REFERENCES

[1] R. C. de Lamare, “Massive mimo systems: Signal processing challenges and future trends,” URSI Radio Science Bulletin, vol. 2013, no. 347, pp. 8–20, 2013.

[2] W. Zhang, H. Ren, C. Pan, M. Chen, R. C. de Lamare, B. Du,
and J. Dai, “Large-scale antenna systems with ul/dl hardware mismatch: Achievable rates analysis and calibration,” *IEEE Transactions on Communications*, vol. 63, no. 4, pp. 1216–1229, 2015.

[3] M. Shafi, A. F. Molisch, P. J. Smith, T. Haustein, P. Zhu, P. De Silva, F. Tufvesson, A. Benjebbour, and G. Wunder, “5G: A tutorial overview of standards, trials, challenges, deployment, and practice,” *IEEE Journal on Selected Areas in Communications*, vol. 35, no. 6, pp. 1201–1221, June 2017.

[4] Q. C. Li, H. Niu, A. T. Papathanassiou, and G. Wu, “5G network capacity: Key elements and technologies,” *IEEE Vehicular Technology Magazine*, vol. 9, no. 1, pp. 71–78, Mar. 2014.

[5] Q. H. Spencer, A. L. Swindlehurst, and M. Haardt, “Zero-forcing methods for downlink spatial multiplexing in multiuser mimo channels,” *IEEE Transactions on Signal Processing*, vol. 52, no. 2, pp. 461–471, 2004.

[6] V. Stankovic and M. Haardt, “Generalized design of multiuser mimo precoding matrices,” *IEEE Transactions on Wireless Communications*, vol. 7, no. 3, pp. 953–961, 2008.

[7] H. Sung, S. Lee, and I. Lee, “Generalized channel inversion methods for multiuser mimo systems,” *IEEE Transactions on Communications*, vol. 57, no. 11, pp. 3489–3499, 2009.

[8] K. Zu and R. C. de Lamare, “Low-complexity lattice reduction-aided regularized block diagonalization for mimo systems,” *IEEE Communications Letters*, vol. 16, no. 6, pp. 925–928, 2012.

[9] K. Zu, R. C. de Lamare, and M. Haardt, “Generalized design of low-complexity block diagonalization type precoding algorithms for multiuser mimo systems,” *IEEE Transactions on Communications*, vol. 61, no. 10, pp. 4232–4242, 2013.

[10] W. Zhang, R. C. de Lamare, C. Pan, M. Chen, J. Dai, B. Wu, and X. Bao, “Widely linear precoding for large-scale mimo with iqi: Algorithms and performance analysis,” *IEEE Transactions on Wireless Communications*, vol. 16, no. 5, pp. 3298–3312, 2017.

[11] A. R. Flores, R. C. de Lamare, and B. Clerckx, “Linear precoding and stream combining for rate splitting in multiuser mimo systems,” *IEEE Communications Letters*, vol. 24, no. 4, pp. 890–894, 2020.

[12] Y. Cai, R. C. de Lamare, L. Yang, and M. Zhao, “Robust mmse precoding based on switched relaying and side information for multiuser mimo relay systems,” *IEEE Transactions on Vehicular Technology*, vol. 64, no. 12, pp. 5677–5687, 2015.

[13] N. Song, W. U. Alokzai, R. C. de Lamare, and M. Haardt, “Adaptive widely linear reduced-rank beamforming based on joint iterative optimization,” *IEEE Signal Processing Letters*, vol. 21, no. 3, pp. 265–269, 2014.

[14] H. Ruan and R. C. de Lamare, “Robust adaptive beamforming using a low-complexity shrinkage-based mismatch estimation algorithm,” *IEEE Signal Processing Letters*, vol. 21, no. 1, pp. 60–64, 2014.

[15] H. Ruan and R. C. de Lamare, “Robust adaptive beamforming based on low-rank and cross-correlation techniques,” *IEEE Transactions on Signal Processing*, vol. 64, no. 15, pp. 3919–3932, 2016.

[16] H. Ruan and R. C. de Lamare, “Distributed robust beamforming based on low-rank and cross-correlation techniques: Design and analysis,” *IEEE Transactions on Signal Processing*, vol. 67, no. 24, pp. 6411–6423, 2019.

[17] K. Zu, R. C. de Lamare, and M. Haardt, “Multi-branch tomlinson-harashima precoding design for mu-mimo systems: Theory and algorithms,” *IEEE Transactions on Communications*, vol. 62, no. 3, pp. 939–951, 2014.

[18] L. Zhang, Y. Cai, R. C. de Lamare, and M. Zhao, “Robust multibranch tomlinson-harashima precoding design in amplify-and-forward mimo relay systems,” *IEEE Transactions on Communications*, vol. 62, no. 10, pp. 3476–3490, 2014.

[19] A. R. Flores, R. C. De Lamare, and B. Clerckx, “Tomlinson-harashima precoded rate-splitting with streaming combining for mu-mimo systems,” *IEEE Transactions on Communications*, pp. 1–1, 2021.

[20] L. T. N. Landau and R. C. de Lamare, “Branch-and-bound precoding for multiuser mimo systems with 1-bit quantization,” *IEEE Wireless Communications Letters*, vol. 6, no. 6, pp. 770–773, 2017.

[21] J. Gu, R. C. de Lamare, and M. Huemer, “Buffer-aided physical-layer networking code with optimal linear code design for cooperative networks,” *IEEE Transactions on Communications*, vol. 66, no. 6, pp. 2560–2575, 2018.

[22] Y. Jiang, Y. Zou, H. Guo, T. A. Tsiftsis, M. R. Bhatnagar, R. C. de Lamare, and Y. D. Yao, “Joint power and bandwidth allocation for energy-efficient heterogeneous cellular networks,” *IEEE Transactions on Communications*, vol. 67, no. 9, pp. 6168–6178, 2019.

[23] X. Lu and R. C. d. Lamare, “Opportunistic relaying and jamming based on secrecy-rate maximization for multiuser buffer-aided relay systems,” *IEEE Transactions on Vehicular Technology*, vol. 69, no. 12, pp. 15269–15283, 2020.

[24] V. M. T. Palhares, A. Flores, and R. C. De Lamare, “Robust mmse precoding and power allocation for cell-free massive mimo systems,” *IEEE Transactions on Vehicular Technology*, pp. 1–1, 2021.

[25] Silvio F. B. Pinto and Rodrigo C. de Lamare, “Block diagonalization precoding and power allocation for multiple-antenna systems with coarsely quantized signals,” *IEEE Transactions on Communications*, vol. 69, no. 10, pp. 6793–6807, 2021.

[26] R. C. de Lamare and R. Sampaio-Neto, “Adaptive mber decision feedback multiuser receivers in frequency selective fading channels,” *IEEE Communications Letters*, vol. 7, no. 2, pp. 73–75, 2003.

[27] R. C. De Lamare, R. Sampaio-Neto, and A. Hjorungnes, “Joint iterative interference cancellation and parameter estimation for cdma systems,” *IEEE Communications Letters*, vol. 11, no. 12, pp. 916–918, 2007.

[28] R. C. De Lamare and R. Sampaio-Neto, “Minimum mean-squared error iterative successive parallel arbitrated decision feedback detectors for ds-cdma systems,” *IEEE Transactions on Communications*, vol. 56, no. 5, pp. 778–789, 2008.

[29] Y. Cai and R. C. de Lamare, “Space-time adaptive mmse multiuser decision feedback detectors with multiple-feedback interference cancellation for cdma systems,” *IEEE Transactions on Vehicular Technology*, vol. 58, no. 8, pp. 4129–4140, 2009.

[30] R. C. de Lamare and R. Sampaio-Neto, “Reduced-rank space-time adaptive interference suppression with joint iterative least squares algorithms for spread-spectrum systems,” *IEEE Transactions on Vehicular Technology*, vol. 59, no. 3, pp. 1217–1228, 2010.
[31] Y. Cai and R. C. de Lamare, “Space-time adaptive mmse multiuser decision feedback detectors with multiple-feedback interference cancellation for cdma systems,” IEEE Transactions on Vehicular Technology, vol. 58, no. 8, pp. 4129–4140, 2009.

[32] P. Li and R. C. De Lamare, “Adaptive decision-feedback detection with constellation constraints for mimo systems,” IEEE Transactions on Vehicular Technology, vol. 61, no. 2, pp. 853–859, 2012.

[33] R. C. de Lamare, “Adaptive and iterative multi-branch mmse decision feedback detection algorithms for multi-antenna systems,” IEEE Transactions on Wireless Communications, vol. 12, no. 10, pp. 5294–5308, 2013.

[34] P. Li and R. C. de Lamare, “Distributed iterative detection with reduced message passing for networked mimo cellular systems,” IEEE Transactions on Vehicular Technology, vol. 63, no. 6, pp. 2947–2954, 2014.

[35] Y. Cai, R. C. de Lamare, B. Champagne, B. Qin, and M. Zhao, “Adaptive reduced-rank receive processing based on minimum symbol-error-rate criterion for large-scale multiple-antenna systems,” IEEE Transactions on Communications, vol. 63, no. 11, pp. 4185–4201, 2015.

[36] R. C. de Lamare and R. Sampaio-Neto, “Adaptive reduced-rank processing based on joint and iterative interpolation, decimation, and filtering,” IEEE Transactions on Signal Processing, vol. 57, no. 7, pp. 2503–2514, 2009.

[37] A. G. D. Uchoa, C. T. Healy, and R. C. de Lamare, “Iterative detection and decoding algorithms for mimo systems in block-fading channels using ldpc codes,” IEEE Transactions on Vehicular Technology, vol. 65, no. 4, pp. 2735–2741, 2016.

[38] Z. Shao, R. C. de Lamare, and L. T. N. Landau, “Iterative detection and decoding for large-scale multiple-antenna systems with 1-bit adcs,” IEEE Wireless Communications Letters, vol. 7, no. 3, pp. 476–479, 2018.

[39] Z. Shao, L. T. N. Landau, and R. C. de Lamare, “Dynamic oversampling for 1-bit adcs in large-scale multiple-antenna systems,” IEEE Transactions on Communications, pp. 1–1, 2021.

[40] R. B. Di Renna, C. Bockelmann, R. C. de Lamare, and A. Dekorsy, “Detection techniques for massive machine-type communications: Challenges and solutions,” IEEE Access, vol. 8, pp. 180928–180954, 2020.

[41] R. B. Di Renna and R. C. de Lamare, “Adaptive activity-aware iterative detection for massive machine-type communications,” IEEE Wireless Communications Letters, vol. 8, no. 6, pp. 1631–1634, 2019.

[42] R. B. Di Renna and R. C. de Lamare, “Iterative list detection and decoding for massive machine-type communications,” IEEE Transactions on Communications, vol. 68, no. 10, pp. 6276–6288, 2020.

[43] R. B. Di Renna and R. C. de Lamare, “Dynamic message scheduling based on activity-aware residual belief propagation for asynchronous mmse,” IEEE Wireless Communications Letters, pp. 1–1, 2021.

[44] F. L. Duarte and R. C. de Lamare, “Cloud-driven multi-way multiple-antenna relay systems: Joint detection, best-user-link selection and analysis,” IEEE Transactions on Communications, vol. 68, no. 6, pp. 3342–3354, 2020.

[45] C. T. Healy and R. C. de Lamare, “Decoder-optimised progressive edge growth algorithms for the design of ldpc codes with low error floors,” IEEE Communications Letters, vol. 16, no. 6, pp. 889–892, 2012.

[46] C. T. Healy and R. C. de Lamare, “Design of ldpc codes based on multipath emd strategies for progressive edge growth,” IEEE Transactions on Communications, vol. 64, no. 8, pp. 3208–3219, 2016.

[47] J. Liu and R. C. de Lamare, “Low-latency reweighted belief propagation decoding for ldpc codes,” IEEE Communications Letters, vol. 16, no. 10, pp. 1660–1663, 2012.

[48] Z. Luo and S. Zhang, “Dynamic spectrum management: Complexity and duality,” IEEE Journal of Selected Topics in Signal Processing, vol. 2, no. 1, pp. 57–73, Feb. 2008.

[49] Y. Liu, Y. Dai, and Z. Luo, “Coordinated beamforming for mimo interference channel: Complexity analysis and efficient algorithms,” IEEE Transactions on Signal Processing, vol. 59, no. 3, pp. 1142–1157, Mar. 2011.

[50] W. Utschick and J. Brehmer, “Monotonic optimization framework for coordinated beamforming in multicell networks,” IEEE Transactions on Signal Processing, vol. 60, no. 4, pp. 1899–1909, Apr. 2012.

[51] M. Schubert and H. Boche, “Solution of the multiuser downlink beamforming problem with individual SINR constraints,” IEEE Transactions on Vehicular Technology, vol. 53, no. 1, pp. 18–28, Jan. 2004.

[52] M. Codreanu, A. Toli, M. Juntti, and M. Latva-aho, “Joint design of Tx-Rx beamformers in MIMO downlink channel,” IEEE Transactions on Signal Processing, vol. 55, no. 9, pp. 4639–4655, Sept. 2007.

[53] C. W. Tan, M. Chiang, and R. Srikant, “Maximizing sum rate and minimizing MSE on multiuser downlink: Optimality, fast algorithms and equivalence via max-min SINR,” IEEE Transactions on Signal Processing, vol. 59, no. 12, pp. 6127–6143, Dec. 2011.

[54] T. Wang, R. C. de Lamare, and A. Schmeink, “Alternating optimization algorithms for power adjustment and receive filter design in multihop wireless sensor networks,” IEEE Transactions on Vehicular Technology, vol. 64, no. 1, pp. 173–184, Jan. 2015.

[55] Q. Shi, M. Razaviyayn, Z. Luo, and C. He, “An iteratively weighted mmse approach to distributed sum-utility maximization for a mimo interfering broadcast channel,” IEEE Transactions on Signal Processing, vol. 59, no. 9, pp. 4331–4340, Sept. 2011.

[56] E. Bjornson, N. Jalden, M. Bengtsson, and B. Ottersten, “Optimality properties, distributed strategies, and measurement-based evaluation of coordinated multicell OFDMA transmission,” IEEE Transactions on Signal Processing, vol. 59, no. 12, pp. 6086–6101, Dec. 2011.

[57] D. P. Palomar and J. R. Fonollosa, “Practical algorithms for a family of waterfilling solutions,” IEEE Transactions on Signal Processing, vol. 53, no. 2, pp. 686–695, 2005.

[58] S. S. Christensen, R. Agarwal, E. De Carvalho, and J. M. Cioffi, “Weighted sum-rate maximization using weighted mmse for mimo-be beamforming designweighted sum-rate maximization using weighted mmse for mimo-be beamforming design,” IEEE Transactions on Wireless Communications, vol. 7, no. 12, pp. 4792–4799, Dec. 2008.
[59] K. Shen and W. Yu, “Ieee transactions on signal processing,”
Fractional Programming for Communication Systems-Part I:
Power Control and Beamforming, vol. 66, no. 10, pp. 2616–2630, May 2018.

[60] S. Chakraborty, Ö. T. Demir, E. Björnson, and P. Giselsson,
“Efficient downlink power allocation algorithms for cell-free
massive mimo systems,” IEEE Open Journal of the Communications Society, vol. 2, pp. 168–186, 2021.

[61] V. M. T. Palhares, R. C. de Lamare, A. R. Flores, and L. T. N Landau,
“Iterative AP selection, MMSE precoding and power
allocation in cell-free massive MIMO systems,” IET Communications, vol. 14, no. 22, pp. 3996–4006, Dec. 2020.

[62] E. Castañeda, A. Silva, A. Gameiro, and M. Kountouris,
“An overview on resource allocation techniques for multi-user
mimo systems,” IEEE Communications Surveys & Tutorials,
vol. 19, no. 1, pp. 239–284, 2017.

[63] D. Bartolome and A. I. Perez-Neira.
“Spatial scheduling in multiuser wireless systems: from power allocation to admission control,”
IEEE Transactions on Wireless Communications, vol. 5, no. 8, pp. 2082–2091, Aug. 2006.

[64] M. Vu and A. Paulraj.
“MIMO wireless linear precoding,”
IEEE Signal Processing Magazine, vol. 24, no. 5, pp. 86–105, Sept. 2007.

[65] S. A. Vorobyov, A. B. Gershman, and Zhi-Quan Luo.
“Robust adaptive beamforming using worst-case performance optimization: a solution to the signal mismatch problem,”
IEEE Transactions on Signal Processing, vol. 51, no. 2, pp. 313–324, Feb. 2003.

[66] Z. L. Yu, Z. Gu, J. Zhou, Y. Li, W. Ser, and M. H. Er.
“A robust adaptive beamformer based on worst-case semi-definite programming,”
IEEE Transactions on Signal Processing, vol. 58, no. 11, pp. 5914–5919, Nov. 2010.

[67] H. Ruan and R. C. de Lamare.
“Distributed robust beamforming based on low-rank and cross-correlation techniques: Design and analysis,”
IEEE Transactions on Signal Processing, vol. 67, no. 24, pp. 6411–6423, Dec. 2019.

[68] M. Joham, W. Utschick, and J. A. Nossek.
“Linear transmit processing in MIMO communications systems,”
IEEE Transactions on Signal Processing, vol. 53, no. 8, pp. 2700–2712, Aug. 2005.