Performance Optimization of Iterative Receiver for Wireless Communications Based on Realistic Channel Conditions

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Abstract

Adopting orthogonal frequency division multiplexing (OFDM) to low-density parity check (LDPC) coded Multiple-input multiple-output (MIMO) is attractive scheme for wireless communication systems. An iterative receiver design for LDPC coded MIMO-OFDM system is proposed as the foundation for enhancing the wireless link performance can deliver the coverage, speed, throughput and reliability. However, in previous works, evaluations are basically assumed for a certain channel scenario and it is inefficient in incorporating different channel scenarios. The aim of this paper is to improve the system range for equivalent error rate, while not significantly increasing system complexity compared to conventional iterative receiver solution under realistic channel environment. We show that our proposed iteration adaptation at receiver can considerably adopt the system to realistic change environment, and reach very high reliability. Simulations of our optimization reveal superior error rate performance and lower computational cost vs. conventional LDPC coded MIMO OFDM system. Our simulation results also capture the effects of realistic vs. typical channel fading types (i.e., Rician vs. Rayleigh, respectively) and fading parameter models (average vs. random azimuth spread and K factor) on system performance and complexity.

Keywords: MIMO-OFDM, LDPC, Iterative receiver, Realistic channel fading

1. Introduction

Multiple-input multiple-output (MIMO) wireless communications systems can improve transmission reliability through diversity and array gain, and the data rate through multiplexing gain. The evolution of the MIMO concept has been punctuated by several landmark forays into its benefits and challenges [1][2][3].

In actual environments, fluctuating channel conditions challenge the design of a consistently-optimal receiver. There have been numerous attempts to maximize performance for minimum computational complexity, by adapting signal processing to the channel requirements. Among them, iterative receivers process the received signals in detector and decoder to improve system performance [4]. Furthermore, efficient channel coding schemes have been shown to improve the performance of MIMO OFDM systems [5][6][7]. LDPC code, with its efficient iterative decoding, has been widely used in WLANs, WIMAX etc. Combining the iterative receiver with LDPC decoding by using channel state information and interference feature feedback from previous iteration can improve MIMO OFDM performance [8].

To the best of our knowledge, MIMO OFDM iterative receiver performance has so far only been evaluated for typical or extreme channel parameter assumptions[9], e.g., fixed azimuth spread (AS) and K-factor. This approach can significantly distort performance indications[10]. Researchers only recently looked into the realistic channel model analysis for MIMO (OFDM) wireless communications systems. However, realistic channel simulations are very important to accuracy predict the actual MIMO (OFDM) performance. The European project WINNER II [11] has measured the distribution for different scenarios, allowing for realistic tests of MIMO OFDM channel condition. Based on our previous analysis [12], we analyze MIMO systems in correlated Rician fading channel, and compare performance for unrealistic and realistic channel models and parameter settings.

The major objective of this paper is to show that the optimized iteration selection for iterative executing detection and LDPC decoding that can approach the performance of the conventional fixed-iteration-number receiver and reduce receiver complexity for realistic Rician fading. In this paper, we evaluate MIMO-OFDM realistically, i.e., for measurement-based AS and K distribution and correlation, and average the total system performance for various wireless communications channel scenarios. Deriving from the fundamental performance approach for LDPC code [13], we focus on the performance improvement from combining iterative interference cancelation detection with LDPC decoding and reduce the numerical complexity of the MIMO-OFDM receiver. Using instantaneous channel state information and feedback information from previous decoder soft-output, can yield a good compromise between complexity and performance. The active-set receiver outputs a soft replica update related to information from decoder. Then, by efficient use of the log-likelihood ratio (LLR) tradeoff between detector and decoder for the received data, the optimized receiver selects appropriate iteration numbers for detection and decoding for the channel condition.

This paper is organized as follows. Section 2 introduces our system model. Section 3 describes the optimized iterative receiver based on instantaneous channel state information and decoding soft replica information and LDPC code design for realistic Rician fading channel. Section 4 shows simulation results and compare the optimized and conventional approaches.

Notation: Scalars, vectors, and matrices are represented in lowercase italics, boldface lowercase, and boldface uppercase, respectively, e.g., a, $\mathbf{a}$, and $\mathbf{A}$; $\mathbf{a} \sim \mathcal{N}_c(\bar{\mathbf{a}}, \mathbf{A})$ indicates that $\mathbf{a}$ is a complex-valued circularly-symmetric random vector[2] of Gaussian distribution with mean $\bar{\mathbf{a}}$ and covariance $\mathbf{A}$; $\psi \sim \mathcal{N}(0, 1)$ indicates that real-valued scalar ψ is a random variable of Gaussian distribution with zero-mean and unit variance; subscripts $\cdot_\mathrm{d}$ and $\cdot_\mathrm{r}$ identify, respectively, the deterministic (mean) and random components of a scalar or vector; index $\cdot_\mathrm{n}$ indicates a normalized variable; $i = 1 : N$ stands for the enumeration $i = 1, 2, \cdots N$; the superscripts $\cdot^{\mathcal{T}}$ and $\cdot^{\mathcal{H}}$ stand for transpose and Hermitian (complex-conjugate) transpose. $\|\cdot\|$ stands for the Euclidean vector norm; $\mathbb{E}\{\cdot\}$ denotes statistical average.

2. Signal and Channel Models

2.1. Signal Model

Let us consider a single-user MIMO OFDM LDPC system with N_R transmit antennas and N_T receive antennas as shown in Fig. 1. The base station transmits the $N_\mathrm{T} \times 1$ signal vector $\mathbf{x}$. The radio channel between

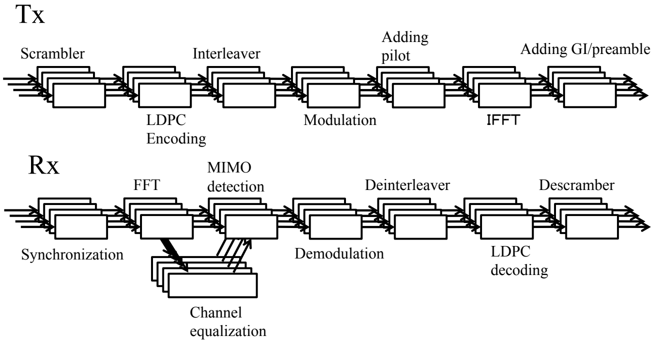

Figure 1: QC-LDPC coded MIMO-OFDM system block diagram model

the base station and the receiving mobile station is represented by matrix $\mathbf{H}$ of size $N_\mathrm{R} \times N_\mathrm{T}$. Then, the received signal, after fast Fourier transform (FFT), can be represented as the $N_\mathrm{R} \times 1$ complex-valued vector [2]:

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}, \tag{1}$$

where $\mathbf{n}$ is temporally- and spatially-white, circularly-symmetric, zero-mean, complex Gaussian with variance N_0, i.e., $\mathbf{n} \sim \mathcal{N}_c(0, N_0 \mathbf{I}_{N_\mathrm{R}})$.

2.2. Channel Fading Model

Let us denote the deterministic and random components of $\mathbf{H}$ as $\mathbf{H}_\mathrm{d}$ and $\mathbf{H}_\mathrm{r}$, respectively, so that $\mathbf{H} = \mathbf{H}_\mathrm{d} + \mathbf{H}_\mathrm{r}$. The channel matrix can then be written further as:

$$\mathbf{H} = \sqrt{\frac{K}{K+1}}\mathbf{H}_\mathrm{d,n} + \sqrt{\frac{1}{K+1}}\mathbf{H}_\mathrm{r,n}, \tag{2}$$

where $\mathbf{H}_\mathrm{d,n}$ and $\mathbf{H}_\mathrm{r,n}$ are the normalized deterministic and random components of the channel matrix, respectively, i.e., $\|\mathbf{H}_\mathrm{d,n}\|^2 = N_\mathrm{T} N_\mathrm{R}$, and $\mathbb{E}\{|\,[\mathbf{H}_\mathrm{r,n}]_{i,j}\,|^2\} = 1$, $\forall i = 1 : N_\mathrm{R}$, $j = 1 : N_\mathrm{T}$. Thus, we can define the power ratio of $\mathbf{H}_\mathrm{d}$ and $\mathbf{H}_\mathrm{r}$, i.e., the Rician K-factor [2] as

$$K = \frac{\|\mathbf{H}_\mathrm{d}\|^2}{\mathbb{E}\{\|\,[\mathbf{H}_\mathrm{r}\|^2\}} = \frac{\frac{K}{K+1}\|\mathbf{H}_\mathrm{d,n}\|^2}{\frac{1}{K+1}\mathbb{E}\{|\,[\mathbf{H}_\mathrm{r,n}]\,|^2\}}. \tag{3}$$

For $K = 0$, the channel fading is described by the Rayleigh distribution. Otherwise, the channel fading is described by the Rice distribution [1]. In this work, we assume that $\mathbf{H}_\mathrm{d}$ is rank-one, which is realistic when the transmitter–receiver distance is much larger than the antenna inter-element distance [2].

Let us consider the downlink from a base-station situated above surrounding scatterers to a user surrounded by scatterers. Then, the rows of $\mathbf{H}_\mathrm{r,n}$ can be assumed mutually uncorrelated (and, thus, independent). On the other hand, let us assume that the columns are correlated, e.g., due to limited base-station antenna interelement distance and azimuth spread (AS). Finally, let us assume that each row in $\mathbf{H}_{r,n}$ has the same, $N_T \times N_T$, covariance matrix $\frac{1}{K+1}\mathbf{R}_T$. Then, we can write $\mathbf{H}_{r,n} = \mathbf{H}_w \mathbf{R}_T^{1/2}$, where $\mathbf{H}_w$ has independent, circularly-symmetric, complex-Gaussian, zero-mean, unit-variance elements[2]. Given the AS, $\mathbf{R}_T$ can be computed for realistic Laplacian power azimuth spectrum (PAS) as in [14][15].

2.3. Statistical Models of Azimuth Spread and K-Factor

Theoretical 802.11n models evaluation suffers from limited practical relevance. WINNER project measured and modeled the radio channel extensively in a wide range of scenarios. Their models are the most comprehensive models available for wireless communication conditions. Different from conventional 802.11n approved channel models with fixed scenario parameter setup, WINNER developed statistical models for fading, and found there is always deterministic component existing in realistic channel conditions.

For example, the WINNER II project found Rician fading in most scenarios and modeled the measured K-factor as a lognormally distributed random variable, e.g., for scenario A1 (indoor office/residential) and line-of-sight (LOS) conditions as [11]:

$$K = 10^{0.1\,(7+6\psi)}, \quad \psi \sim \mathcal{N}(0,1), \tag{4}$$

i.e., the K-factor in dB has mean 7 and standard deviation 6, respectively.

On the other hand, intended-signal power arrives with azimuth angle dispersion that is typically modeled by the Laplacian PAS. The realistic Laplacian PAS model[14][11] has been used for the simulation results shown later in this paper. The AS is the root mean-square of the PAS, and affects antenna correlation[2][16]. WINNER II also modeled the base-station AS (expressed in degrees) as a lognormally distributed random variable, e.g., for scenario A1[11]:

$$AS = 10^{1.64+0.31\chi}, \quad \chi \sim \mathcal{N}(0,1), \tag{5}$$

i.e., the AS mean and standard deviation are about 56° and 45°, respectively.

The WINNER II measurements also found that AS and K can be correlated[11]. Hereafter, ρ represents the measured correlation of ψ and χ from (4) and (5). Depending on the scenario, this correlation can be negative, zero, or positive The numerical results shown later in this paper are for scenarios A1 and C2, which are described in Table 1 based on [11].

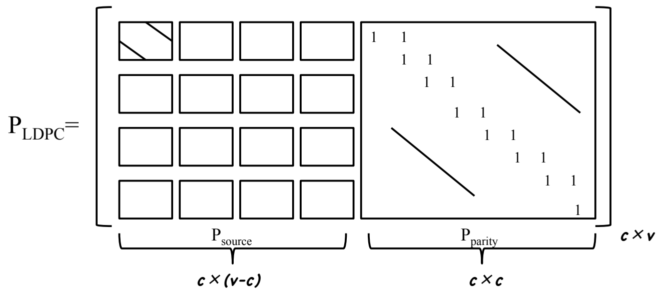

Figure 2: LDPC parity-check matrix structure

3. Iterative Receiver

3.1. Iterative LDPC Decoding (Inner Loop)

LDPC code is a binary linear block code described by a sparse parity-check matrix, i.e., with many zeros and only a few ones (nodes)[17, Fig. 2.1]. Its performance approaches the theoretical limit set by Shannon's theorem [17]. Since LDPC coding helps achieve high transmission reliability, it is widely considered for future-generation wireless communications systems [6][7].

Quasi-cyclic (QC) LDPC codes form a class of LDPC codes with efficient encoding and low-complexity decoding due to simple parity-check matrix structure[18][19]. In[20] we have shown that QC-LDPC can approach the bit-error-rate performance of random-structured LDPC [17]. Fig. 2 depicts the QC-LDPC parity-check matrix, $\mathbf{P}_{\text{LDPC}}$, of size $c \times v$, where c is the number of parity-check bits, and v is the codeword length. The coding rate is then $R = (v-c)/v$. In $\mathbf{P}_{\text{source}}$ each sub-block matrix is quasi-cyclic[21], whereas matrix $\mathbf{P}_{\text{parity}}$ is double-diagonal.

For QC-LDPC there are available a number of soft-output decoding algorithms, e.g., the min-sum algorithm (MSA), which has been preferred for many practical applications since it offers comparable decoding performance compared to that of conventional belief-propagation LDPC decoding. MSA shows extremely efficient (high reliability, low complexity) for LDPC decoding [22][23], whereby a soft-input/soft-output approach is applied iteratively to improve decoding reliability based on parity-check sums computed from detected symbols and the sparse parity-check matrix.

Fig. 3 depicts, in the right-hand side, the QC-LDPC decoder, with the variable node decoding (VND) and check node decoding (CND) blocks. These blocks employ MSA as described shortly. First, we define the set of bits that participate in parity check c as $\mathcal{V}(c) = \{v : \mathbf{P}_{\text{LDPC}} = 1\}$, and the set of parity checks in which

Table 1: Base-station AS and K statistics, for LOS[11]

Scenario	AS [°]	K	ρ
A1: indoor office/residential	$10^{1.64+0.31\chi}$	$10^{0.1(7+6\psi)}$	-0.6
C2: typical urban macrocell	$10^{1.00+0.25\chi}$	$10^{0.1(7+3\psi)}$	$+0.1$

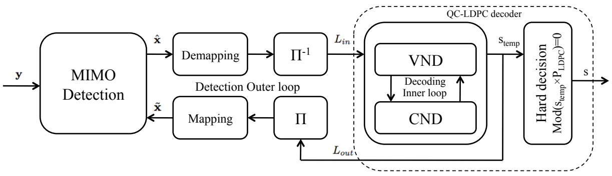

Figure 3: MIMO-OFDM QC-LDPC iterative receiver model

variable bits v participates as $C(v) = \{c : \mathbf{P}_{\text{LDPC}} = 1\}$. $\mathcal{V}(c)$ denotes variable bits v excluded by $\mathcal{V}(c) \setminus v$, and $C(v)$ denotes check c excluded by $C(v) \setminus c$. Hereafter, L_{in} and L_{out} represent the *a priori* and *a posteriori* soft-input/soft-output log-likelihood ratios (LLRs), respectively, and β represents the extrinsic information. Further, α and β represent the variable-to-check node message and check-to-variable node message, respectively. Finally, index j indicates decoding iteration number.

The formulation of MSA is as shown in Algorithm 1([23]).

Algorithm 1 LDPC iterative decoding

Initialization: $\alpha_{(c,v),0} = L_{\text{in}}$, where α is the node exchange tentative parameter and L_{in} is the soft-input log-likelihood value;
for $j = 1 : J_{max}$ or convergence to the hard decision **do**
    Check-to-variable message updating phase: $|\beta_{(c,v),j}| = \prod_{v' \in \mathcal{V}(c) \setminus v} \text{sign}(\alpha_{(c,v'),(j-1)}) \min_{v' \in \mathcal{V}(c) \setminus v}\{|\alpha_{(c,v'),(j-1)}|\}$;
    Variable-to-check message updating phase: $L_{\text{out},(v,j)} = L_{\text{in}} + L_E = L_{\text{in}} + \sum_{c \in C(v)} \beta_{(c,v),j}$; $\alpha_{(c,v),j} = L_{\text{out},(v,j)} - \beta_{(c,v),j}$;
    Hard decision for each information bit: $s_{\text{temp}} = \text{sign}(L_{\text{out},(v,j)})$
    Parity check for all the decoded information bits: $\mod 2(\mathbf{s}_{\text{temp}} \times \mathbf{P}_{\text{LDPC}}^T) = 0$
    if the $\mathbf{s}_{\text{temp}}$ satisfies the parity check **then**
        output the decoded bits as $\mathbf{s} = \mathbf{s}_{\text{temp}}$,
    else
        return to continue the decoding iterations
    end if
end for

3.2. Iterative Detection (Outer Loop)

The challenge detecting in spatially-multiplexed streams of symbols in MIMO is to design a low-complexity approach that can efficiently remove interstream interference, in order to approach the interference-free bound. The iterative receiver approach has been successfully extended to joint detection and decoding [24][25][26].

Fig. 3 shows how the MIMO detection block connects with the decoding block to form a joint detection–decoding architecture. Hereafter, we assume that the spatially-multiplexed streams are detected using the minimum mean square error (MMSE) approach. The MMSE detector outputs are then decoded by a single QC-LDPC soft-inputs/soft-output decoder. In each iteration, the soft-outputs of the decoder are used to update the LLRs of the transmitted signals that are then used in the detector to compute the symbol estimate.

The MMSE detection approach[2] optimally reduces the difference between the transmitted vector and

$$\hat{\mathbf{x}} = \mathbf{W}\mathbf{y}. \tag{6}$$

Then, it can be shown that the weight matrix $\mathbf{W}$ is given by:

$$\mathbf{W} = (\mathbf{H}^{\mathcal{H}}\mathbf{H} + N_0\mathbf{I}_{N_{\text{R}}})^{-1}\mathbf{H}^{\mathcal{H}}. \tag{7}$$

The conventional iterative receiver uses MMSE detection updated by adapting an interpolation matrix $\mathbf{D}$ to weight matrix calculation. This $\mathbf{D}$ matrix contains the transmit signal replica obtained after decoding, i.e., $\tilde{\mathbf{x}}$. Hereafter, m and n index the transmit and receive antennas, respectively. On the other hand, whereas i and j index detection iteration and decoding iteration, respectively. Let $\mathbf{w}_m^{\mathcal{H}}$ represent the mth row of $\mathbf{W}$. Then, we can obtain the soft-estimated transmitted symbol for mth antenna as

$$\hat{x}_{m,i} = \mathbf{w}_{m,i}^{\mathcal{H}}(\mathbf{y} - \mathbf{H}\tilde{\mathbf{x}}_{m,i-1}). \tag{8}$$

Here is a summary of the algorithm, as described in Algorithm 2([4]).

The soft replica for the mth antenna is generated from the *a posteriori* LLR $L_{\text{out}} = L_{\text{in}} + \beta$ that is obtained by the QC-LDPC decoder. Note that L_{out} can be computed not only for binary modulation but for any other $\mathcal{M}$-PSK

Algorithm 2 Conventional iterative detection

for $m = 1 : N_T$ **do**
  $\mathbf{w}_m^{\mathcal{H}} = \mathbf{h}_m^{\mathcal{H}}(\mathbf{H}\mathbf{D}_{m,i-1}\mathbf{H}^{\mathcal{H}} + N_0\mathbf{I}_{N_R})^{-1}$
  $\mathbf{D}_{m,i-1} = \mathrm{diag}\{\triangle_{1,i-1}, \cdots, \triangle_{m-1,i-1}, 1, \triangle_{m+1,i-1}, \cdots, \triangle_{N_T,i-1}\}$, where $\triangle_{m,i-1} = x_{m,i-1} - \tilde{x}_{m,i-1}$.
  $\hat{x}_{m,i} = \mathbf{w}_{m,i}^{\mathcal{H}}(\mathbf{y} - \mathbf{H}\tilde{\mathbf{x}}_{m,i-1})$, where $\tilde{\mathbf{x}}_{m,i-1} = [\tilde{x}_{1,i-1}, \cdots, \tilde{x}_{m-1,i-1}, 0, \tilde{x}_{m+1,i-1}, \cdots, \tilde{x}_{N_T,i-1}]^T$.
end for

modulation. Then, the replica derived from decoding is given by [27]:

$$\tilde{x}_{m,q} = \mathbb{E}\{x_{m,q}\} = \sum_{x_{m,q}\in\mathcal{M}} x_m \prod_{q=1}^{\log_2 \mathcal{M}} 1/[1 + e^{-x_{m,q} L_{\mathrm{out},(v,j)}}] \tag{9}$$

3.3. Proposed Adaptive Joint Iterative Detection–Decoding Approach

Conventional iterative detection–decoding can yield a significant performance gain (in terms of the error rate). However, the detection and decoding steps are executed for fixed number of iterations [28][26].

Since the MMSE solution from (6) suffers from interstream interference [2], we adopt successive interference cancelation (SIC) [29] to mitigate the interference in the first detection iteration loop, which produces a more suitable signal for decoding. The SIC approach — where one stream is treated as target stream whereas remaining streams are treated as interferers and the processing subtracts the interference stream by stream — is as shown in Algorithm 3.

Algorithm 3 Interstream interference cancellation

for $m = 1 : N_T, i = 1$ **do**
  $\hat{x}_{m,i} = \mathbf{w}_m^{\mathcal{H}}\mathbf{y}$
  $\mathbf{y} = \mathbf{y} - \mathbf{h}_m\hat{x}_{m,i}$
  $\mathbf{H} = \mathbf{H}_{-m}$, where $\mathbf{H}_{-m}$ describes deleting the mth column from $\mathbf{H}$
end for

After all streams have been processed, the obtained stream symbol estimates are demodulated to obtain the initial *a priori* LLRs L_{in} for QC-LDPC decoding, as follows [27]:

$$L_{\mathrm{in}} = \log_2 \frac{\Pr\{\hat{x}_m | x_m = 1\}}{\Pr\{\hat{x}_m | x_m = 0\}} = \log_2 \frac{\sum_{\tilde{x}_{m,q}\in x_{m,1}=1} e^{\xi}}{\sum_{\tilde{x}_{m,q}\in x_{m,1}=0} e^{\xi}}, \tag{10}$$

where

$$\xi = -\frac{||y_m - \mathbf{H}\tilde{x}_{m,q}||^2}{N_0} + \frac{1}{2}\sum_{m=1}^{N_{\mathrm{T}}}\sum_{q=1}^{\log_2 M} x_{m,q}L_{out,(v,j)} \tag{11}$$

In practice, the SNR changes with the fading amplitude, which affects error rate performance[13]. Therefore, after the first iteration, we consider adapting the iteration numbers to the actual channel conditions in order to reduce complexity or improve performance. Thus, we found that low SNR calls for more decoding iterations. This is because the LLR from the detector is as well as expected. Then, unnecessary detection iterations can be eliminated. On the other hand, high SNR calls for more detection iterations, in order to cancel interference. Thus, we can use fewer decoding iterations to reduce computational cost. Within the maximum number of iterations, an optimized iteration selection is obtained by comparing signal-to-interference-plus-noise-ratio (SINR $= \mathbf{w}_m^{\mathcal{H}}\mathbf{h}_m$) in detection iterations. The proposed structure is described by Algorithm 4.

Algorithm 4 Dynamic iterative receiver adaptation

Set ($\mathrm{I}_{\max} = 4,\ \mathrm{J}_{\max} = 10$)
while $j < \mathrm{J}_{\max}, i < \mathrm{I}_{\max}$ **do**
  compute $\mathbf{D}_m$ for i-1 iteration
  update each row of weight matrix $\mathbf{w}_m$
  $\mathrm{SINR}_{m,i} = \mathbf{h}_m^{\mathcal{H}}(\mathbf{H}\mathbf{D}_{m,i-1}\mathbf{H}^{\mathcal{H}} + N_0\mathbf{I}_{N_R})^{-1}\mathbf{h}_m$
  estimate transmitted signal $\hat{x}_m$
  compute L_{in} for decoding
  if $\mathrm{SINR}_{m,i} \leqslant \mathrm{SINR}_{m,i-1}$ **then** j++
  else i++
  end if
end while

4. Numerical Results

Reference[30] shows that for more iterations accuracy improves. However, to achieve a certain performance level, a minimum number of iterations is required. This number was obtained by simulations in [31]. Thus, in this paper, we choose the best achievable bit error rate performance with fixed iteration loops as a criterion and try to optimize the iteration loops.

Since most scenarios may actually experience $\mathrm{rank}(\mathbf{H}_{\mathrm{d,n}}) = 1$, we have considered a rank-one deterministic channel matrix in our simulations. For only adapting iterative detection or decoding, by using the method in [31] for an IEEE 802.11n system, that at least five and two iterations are needed for decoding and detection, respectively, for a packet error rate of 10^{-2}. Then, for the bidirectional receiver structure, simulation results are shown for a 4×4 MIMO OFDM system. The modulation is 16-QAM, the code length $c = 832$, the coding rate is $R = 1/2$, and the SNR (i.e., E_b/N_0)

is from 25 dB to 50 dB. We test WINNER II scenarios for the effects on performance of fading type and fading parameter model by considering the following cases:

a) $K = 0$, for Rayleigh fading (unrealistic)

b) K equals to the mean of its lognormal distribution (unrealistic, but such typical values are often considered[1])

c) (AS, K) samples with AS and K lognormally distributed and correlated as in Table 1 (realistic).

In the first simulation iteration, the detection and decoding iteration numbers are set to their minimum mentioned above. Thereafter, for a low SINR we increase the detection iteration number (and maintain the minimum decoding iteration number), whereas for a high SINR we increase decoding iteration number (and maintain the minimum detection iteration number, until the decoding iteration reaches to the maximum number.

For the new optimized iterative receiver, Figs. 4 and 5 show the performance comparison for un/realistic channel models for scenarios A1 and C2, respectively. Fig. 4 shows that Rayleigh fading yields better performance than Rician fading with fixed K-factor. The latter displays somewhat better performance than Rician fading with correlated AS and K.

Fig. 5 shows similar results. However, unlike for scenario A1 (with large AS), the Rayleigh vs. Rician performance gap remains constant with increasing SNR for scenario C2 (with small AS). These results also indicate that the actual performance (average over the AS and K distributions) can be significantly different from the performance measured for average K value.

Let us now compare the performance of the newly-proposed iterative receiver with optimized numbers of detection and decoding iterations with the conventional noniterative receiver [27] and with the iterative receiver with fixed numbers of iterations [27, 28] (40 detection and decoding iterations in total as mentioned in [31] as well). Fig. 6 depicts our results for scenario A1 with randomness AS-K and $\mathrm{rank}(\mathbf{H}_\mathrm{d}) = 1$. Note that the iterative receivers outperform the noniterative receiver by about 2 dB. Furthermore, the optimized iterative receiver approaches the performance of the nonoptimized iterative receiver. Then, Fig. 7 shows $\mathrm{rank}(\mathbf{H}_\mathrm{d})$ = full. A comparison for different fading with randomness AS-K is depicted as well. The performance gap between noniterative and iterative receiver become larger. The optimized iterative receiver plot is overlap with the nonoptimized iterative receiver, which means the optimized iterative receiver performance is viable.

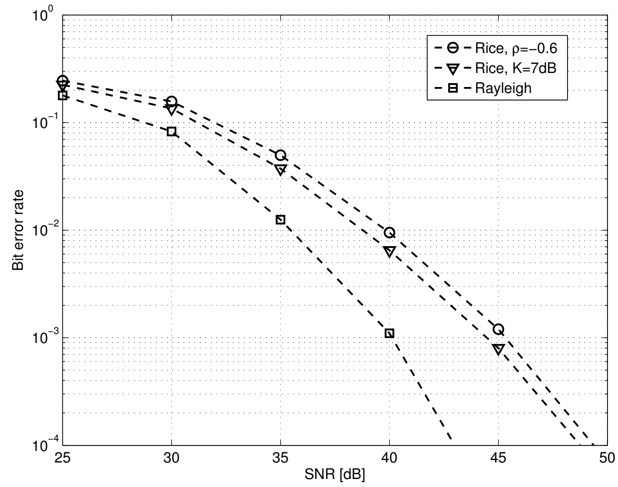

Figure 4: A1 scenario, optimized iterative receiver for unrealistic/realistic fading channels.

We have obtained similar results for scenario C2. Note from these figures that the bit error rate (BER) is higher for scenario C2 than for scenario A1. The mean AS for scenarios A1 and C2 are about 50° and 12°, respectively. This is due to the greater AS leads the transmit power more uniformly as i.i.d. channel (and thus, diversity gain) in the latter case.

For iteration cost, we list the computational iterations for decoding and detection in Tabel 2. Furthermore, the iteration cost is compared between $\mathrm{rank}(\mathbf{H}_\mathrm{d}) = 1/\mathrm{full}$, respectively. Since the fixed K-factor Rician fading behaves similar as correlated AS and K Rician fading, we compare the correlated Rician fading with Rayleigh fading for computation cost performance. Due to the randomness of Rician fading, the iterations for decoding renders sensitively when increasing the SNR. The more iterations of detection is also required for the correlated Rician fading comparing with the typical Rayleigh fading. All the adapted iterative receiver can outperform fixed iteration receiver that executes a constant number of iterations for all SNRs.

5. Conclusion

In this paper, we propose an optimization method for iterative MIMO-OFDM receivers. In particular, we developed efficient LDPC decoding with receiver iterations that are mindful of the data recover accuracy at receiver. We adapt the receiver iterations and LDPC decoding iterations dynamically based on evaluating realistic channel conditions, where a variation of chan-

Table 2: Computational cost for different fading schemes

rank($\mathbf{H}_\mathrm{d}$) = N_T							
SNR		0	5	10	15	20	25
Rayleigh fading	Decoding iteration	10	9	8	8	7	6
	Detection iteration	2	2	2	3	3	3
Rice fading $\rho = -0.6$	Decoding iteration	10	8	8	7	7	5
	Detection iteration	2	2	3	3	3	4
Fixed iteration Receiver	Decoding iteration	10	10	10	10	10	10
	Detection iteration	4	4	4	4	4	4

rank($\mathbf{H}_\mathrm{d}$) = 1							
SNR		25	30	35	40	45	50
Rayleigh fading	Decoding iteration	10	10	9	9	8	7
	Detection iteration	2	2	3	3	3	4
Rice fading $\rho = -0.6$	Decoding iteration	10	9	8	8	6	6
	Detection iteration	2	3	4	4	4	4
Fixed iteration Receiver	Decoding iteration	10	10	10	10	10	10
	Detection iteration	4	4	4	4	4	4

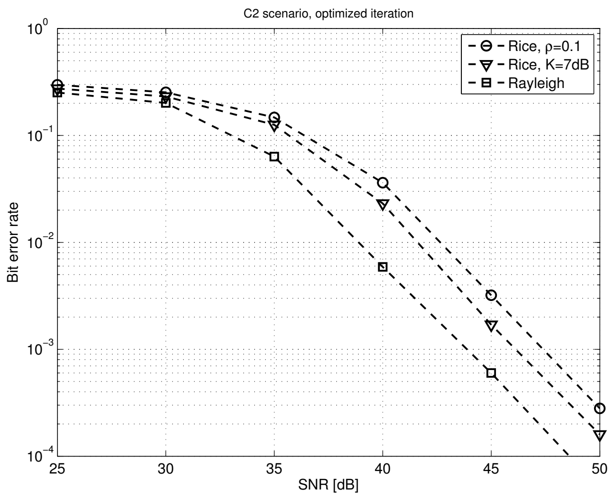

Figure 5: C2 scenario, optimized iterative receiver for unrealistic/realistic fading channels.

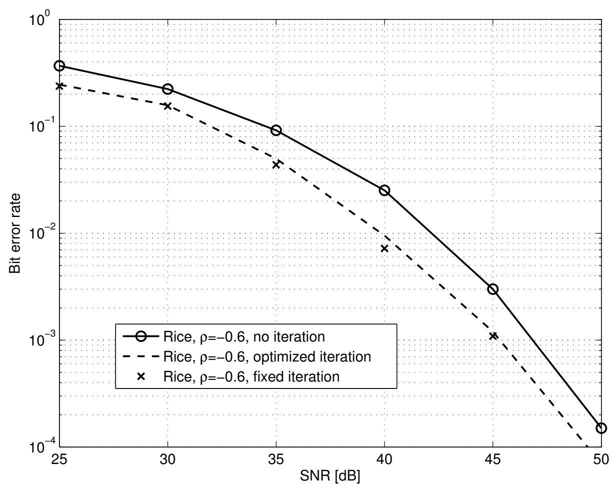

Figure 6: A1 scenario, non/iterative receiver performance comparison for realistic fading model, rank($\mathbf{H}_\mathrm{d}$) = 1.

nel parameters is carefully considered. The results presented highlight the validity of our approach in that ,despite the decreased iterations, we are able to attain close conventional fixed iteration performance but lower computational cost.

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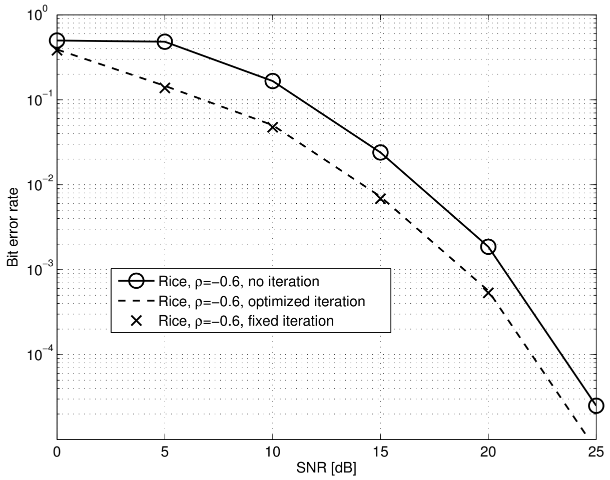

Figure 7: A1 scenario, non/iterative receiver performance comparison for realistic fading model, rank($\mathbf{H}_\mathrm{d}$) = full.

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