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Abstract	This contribution provides a link abstraction methodology for ML receivers based on MMIB metrics developed in C802.16m-07/097
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Link Performance Abstraction for ML Receivers Based on MMIB Metrics

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Purpose

This contribution provides the detailed description of link evaluation methodology for MIMO Maximum Likelihood (ML) receivers. Link performance abstraction using MMIB metrics was proposed for adoption in a previous contribution C802.16m-07/097, which was also reflected in the current draft of the evaluation methodology document. The extension of MMIB-based link abstraction to ML receivers was briefly described in this previous contribution. This contribution provides additional details, relevant functional approximations to allow a simulation study to be conducted. Results are shown verifying the improved performance prediction with these metrics.

Introduction

For SISO systems, a single variable – signal to noise ratio – can be used to obtain reliable mutual information measures. For MIMO spatial multiplexing, with linear receivers such as MMSE receivers, a spatial channel can be split into two equivalent SISO channels for the two symbols transmitted. This simplification arises from the structure of the receiver itself. However, it is well known that the performance of these receivers is suboptimal compared to a maximum likelihood (ML) receiver. It is also well known that implementations with near-ML performance but significantly lower complexity also exist, such as sphere decoding. The performance of such Quasi-ML (QML) solutions can differ significantly from linear receiver performance, especially for specific channel realizations. So, for reliable link performance prediction, a solution targeted at the ML decoder itself is desirable.

ESM based methods such as EESM, cannot be extended to QML receivers without defining separate spatial channels since EESM uses the post-processing CINR seen by each stream. However, in our previous contribution C802.16m-07/097, it was shown that link abstraction can be achieved by using the MIB metrics exclusively, i.e., by mapping MMIB directly to BLER. The task for modeling MIMO-ML performance is then to obtain MMIB functions for the matrix channel that allow us to accurately simulate an ML receiver, without significantly increasing the simulation overhead.

In this contribution, we develop a solution that computes the mutual information per bit given a particular channel matrix realization on 2 transmit and 2 receive antennas, and further express this measure as a function of three real parameters derived from the channel matrix. These functions are applicable as long as the resulting equivalent channel matrix is 2x2. Further, in accordance with the modes supported in the WiMAX profile, the functions derived are applicable to "vertical" encoding, i.e., they yield an average MIB over the two streams. The approach presented can also be adapted to other future forms of MIMO encoding such as "horizontal" encoding.

It was shown in [1] that conditional LLR PDFs can be effectively approximated as a mixture of Gaussian distributions. It will be shown that in MIMO transmission with an ML receiver, the statistics of the Gaussian distributions constituting the LLR PDFs can be approximated as function of the three proposed parameters, which includes the Eigen values. This in turn allows us to approximate MMIB mappings as a sum of basic $J(.)$ functions.

Numerical results are presented for different MCSs considered for 802.16e and show that reliability of the proposed metrics for link performance prediction is close to the SISO MMIB metrics. Results for other suboptimal approaches are also included for comparison.

Optimal Mappings for Non-linear Receivers from Eigen Decomposition

In the previous contribution on MMIB, mutual information is evaluated by assuming that the data symbols are transmitted on separate channel eigen-modes. However, this is only possible when perfect channel knowledge is available at the transmitter and is in general not applicable to non-Gaussian constellations. Other approaches consider linear receivers such as MMSE or SIC receivers. In this section, we propose an approach to optimally compute MIB with the ML receiver.

The received vector for a spatial multiplexing scheme can be represented as

$$\mathbf{y} = \mathbf{Hs} + \mathbf{n} \qquad (1.1)$$

where $\mathbf{y} = [y_1, y_2]^H$ is the received vector on two antennas, $\mathbf{s} = [s_1, s_2]^H$ is the transmitted vector of two QAM symbols, and $\mathbf{n} = [n_1, n_2]^H$ is AWGN where each component is circularly symmetric complex Gaussian with $E[\mathbf{nn}^H] = \sigma_n{}^2 I$,where I is the 2x2 Identity matrix.

The eigenvalue decomposition of $\mathbf{H}^H\mathbf{H}$ can be denoted as $\mathbf{H}^H\mathbf{H} = \mathbf{VDV}^H$, and an equivalent channel model can be obtained as follows

$$\begin{aligned} \mathbf{D}^{-1/2}\mathbf{V}^H\mathbf{H}^H\mathbf{y} &= \mathbf{D}^{1/2}\mathbf{V}^H\mathbf{s} + \mathbf{D}^{-1/2}\mathbf{V}^H\mathbf{H}^H\mathbf{n} \\ \mathbf{y}' &= \mathbf{s}' + \mathbf{n}' \end{aligned} \qquad (1.2)$$

Note that $E[\mathbf{n}'\mathbf{n}'^H] = \sigma_n{}^2 I$. Let us denote $\chi_2 = \chi \text{ x } \chi$ as the hyper-constellation of the MIMO concatenated symbol $\mathbf{s}$, which is a cross-product of two QAM signal constellations represented by χ with 2^m elements (i.e., “m” is the modulation order). Further, denote $\chi_2' = T(\chi_2)$ as the new transformed hyper-constellation obtained by the linear transformation defined by

$$T(\mathbf{s}) = \mathbf{D}^{1/2}\mathbf{V}^H\mathbf{s} \qquad (1.3)$$

The LLR of a bit b_{ij} corresponding to i th antenna (or i th symbol) and j th position in the m -tuple mapped to QAM symbol, is given as follows

$$LLR(b_{ij} \mid \mathbf{y}', \mathbf{H}) = \ln\left(\frac{\sum_{\mathbf{s}:b_{ij}=1} e^{-\frac{\|\mathbf{y}'-\mathbf{D}^{1/2}\mathbf{V}^H\mathbf{s}\|^2}{\sigma_n{}^2}}}{\sum_{\mathbf{s}:b_{ij}=0} e^{-\frac{\|\mathbf{y}'-\mathbf{D}^{1/2}\mathbf{V}^H\mathbf{s}\|^2}{\sigma_n{}^2}}} \right) \qquad (1.4)$$

The mean mutual information per bit of the spatial multiplexing is obtained by averaging over $2m$ bits

$$M(\mathbf{H}) = I(b, LLR \mid \mathbf{H}) = \frac{1}{2m}\sum_{i=1}^{2}\sum_{j=1}^{m} I(b_{ij}, LLR(b_{ij}) \mid \mathbf{H}) \qquad (1.5)$$

MIB can be obtained for each channel random matrix $\mathbf{H}$ by computing the conditional PDFs of LLRs and substituting in the expression for mutual information per bit. However, it is difficult to obtain closed form expressions. In practice, to compute MIB of a particular matrix realization on each subcarrier, we need an efficient approach to approximate this matrix function.

Since $\mathbf{V}$ is a unitary matrix, we have

$$|\mathbf{V}|.|\mathbf{V}| = \begin{pmatrix} p_a & 1-p_a \\ 1-p_a & p_a \end{pmatrix} \quad (1.6)$$

where $|\mathbf{V}|$ denotes the matrix after taking element-wise absolute values, $0 \le p_a \le 1$ and '**.**' represents the operation of element-wise multiplication.

Let us revisit the expression of LLR for BPSK. Specifically, let us look at the LLR expression for the bit transmitted on antenna 1. The LLR is given by

$$\begin{aligned} LLR(b_{11} | \mathbf{y}', \mathbf{H}) &= \ln\left(\frac{\sum_{\mathbf{s}:b_{11}=1} e^{-\frac{\|\mathbf{y}'-\mathbf{D}^{1/2}\mathbf{V}^H\mathbf{s}\|^2}{\sigma_n^2}}}{\sum_{\mathbf{s}:b_{11}=0} e^{-\frac{\|\mathbf{y}'-\mathbf{D}^{1/2}\mathbf{V}^H\mathbf{s}\|^2}{\sigma_n^2}}} \right) \\ &= \ln\left(\frac{e^{-\frac{\|\mathbf{y}'-\mathbf{D}^{1/2}\mathbf{V}^H\begin{bmatrix}-1\\-1\end{bmatrix}\|^2}{\sigma_n^2}} + e^{-\frac{\|\mathbf{y}'-\mathbf{D}^{1/2}\mathbf{V}^H\begin{bmatrix}-1\\+1\end{bmatrix}\|^2}{\sigma_n^2}}}{e^{-\frac{\|\mathbf{y}'-\mathbf{D}^{1/2}\mathbf{V}^H\begin{bmatrix}+1\\-1\end{bmatrix}\|^2}{\sigma_n^2}} + e^{-\frac{\|\mathbf{y}'-\mathbf{D}^{1/2}\mathbf{V}^H\begin{bmatrix}+1\\+1\end{bmatrix}\|^2}{\sigma_n^2}}} \right) \end{aligned} \quad (1.7)$$

The conditional LLR PDF given $b_{11} = 1$ can be expanded as

$$\begin{aligned} p(LLR(b_{11} | \mathbf{y}', \mathbf{H}, b_{11} = 1) = {} & p(b_{21} = 1) p(LLR(b_{11} | \mathbf{y}', \mathbf{H}, b_{11} = 1, b_{21} = 1) \\ & + p(b_{21} = 0) p(LLR(b_{11} | \mathbf{y}', \mathbf{H}, b_{11} = 1, b_{21} = 0) \end{aligned} \quad (1.8)$$

Further, we have

$$p(LLR(b_{11} | \mathbf{y}', \mathbf{H}, b_{11} = 1, b_{21} = 1) = \ln\left(\frac{e^{-\frac{\|\mathbf{n}'\|^2}{\sigma_n^2}} + e^{-\frac{\|\mathbf{D}^{1/2}\mathbf{V}^H\begin{bmatrix}0\\-2\end{bmatrix}+\mathbf{n}'\|^2}{\sigma_n^2}}}{e^{-\frac{\|\mathbf{D}^{1/2}\mathbf{V}^H\begin{bmatrix}-2\\0\end{bmatrix}+\mathbf{n}'\|^2}{\sigma_n^2}} + e^{-\frac{\|\mathbf{D}^{1/2}\mathbf{V}^H\begin{bmatrix}-2\\-2\end{bmatrix}+\mathbf{n}'\|^2}{\sigma_n^2}}} \right) \quad (1.9)$$

Define

$$\mu_{1,1} = -\min\{\| \mathbf{D}^{1/2}\mathbf{V}^H \begin{bmatrix}-1\\0\end{bmatrix} \|^2, \quad \| \mathbf{D}^{1/2}\mathbf{V}^H \begin{bmatrix}-1\\-1\end{bmatrix} \|^2\} \quad (1.10)$$

We then have

$$\begin{aligned} p(LLR(b_{11} | \mathbf{y}', \mathbf{H}, b_{11} = 1, b_{21} = 1) &= \ln\left(\frac{e^{-\frac{\|\mathbf{n}'\|^2}{\sigma_n^2}}}{e^{-\frac{\|2\mu_{1,1}+\mathbf{n}'\|^2}{\sigma_n^2}}} \right) \quad (\text{ High SNR approximation }) \\ &= \frac{4}{\sigma_n^{\ 2}} \mu_{1,1} + n'' \end{aligned} \quad (1.11)$$

where $E[n''^* n''] = \frac{8}{\sigma_n^{\ 4}} \mu_{1,1}$. Let us represent $\mathbf{V}$ as[1]

[1] Such a representation can be obtained by appropriate rotation of the columns

$$\mathbf{V} = \begin{bmatrix} \sqrt{p_a} e^{j\theta} & \sqrt{1-p_a} e^{j\theta} \\ -\sqrt{1-p_a} & \sqrt{p_a} \end{bmatrix} \quad (1.12)$$

We can then obtain

$$\begin{aligned} \| \mathbf{D}^{1/2}\mathbf{V}^H \begin{bmatrix} -1 \\ 0 \end{bmatrix} \| &= \lambda_{\max} p_a + \lambda_{\min}(1-p_a) \\ \| \mathbf{D}^{1/2}\mathbf{V}^H \begin{bmatrix} -1 \\ -1 \end{bmatrix} \| &= \lambda_{\max}\left[1-2\sqrt{p_a(1-p_a)}\cos(\theta)\right] + \lambda_{\min}\left[1+2\sqrt{p_a(1-p_a)}\cos(\theta)\right] \\ &\geq \lambda_{\max}\left[1-2\sqrt{p_a(1-p_a)}\right] + \lambda_{\min}\left[1+2\sqrt{p_a(1-p_a)}\right] \quad \text{(Lower Bound)} \end{aligned} \quad (1.13)$$

Similarly, we can show

$$p(LLR(b_{11} \mid \mathbf{y}', \mathbf{H}, b_{11}=1, b_{21}=0) = \frac{4}{\sigma_n^2}\mu_{1,0} + n'' \quad (1.14)$$

where $\mu_{1,0} = -\min\{\| \mathbf{D}^{1/2}\mathbf{V}^H \begin{bmatrix} -1 \\ 0 \end{bmatrix} \|^2, \quad \| \mathbf{D}^{1/2}\mathbf{V}^H \begin{bmatrix} -1 \\ -2 \end{bmatrix} \|^2\}$ and

$$\begin{aligned} \| \mathbf{D}^{1/2}\mathbf{V}^H \begin{bmatrix} -1 \\ +1 \end{bmatrix} \| &= \lambda_{\max}\left[1+2\sqrt{p_a(1-p_a)}\cos(\theta)\right] + \lambda_{\min}\left[1-2\sqrt{p_a(1-p_a)}\cos(\theta)\right] \\ &\geq \lambda_{\max}\left[1-2\sqrt{p_a(1-p_a)}\right] + \lambda_{\min}\left[1+2\sqrt{p_a(1-p_a)}\right] \end{aligned} \quad (1.15)$$

and similarly

$$p(LLR(b_{21} \mid \mathbf{y}', \mathbf{H}, b_{11}=0, b_{21}=1) = \frac{4}{\sigma_n^2}\mu_{0,1}^2 + n'' \quad (1.16)$$

where $\mu_{0,1} = \min\{\lambda_{\max}(1-p_a) + \lambda_{\min} p_a, \lambda_{\max}\left[1-2\sqrt{p_a(1-p_a)}\cos(\theta)\right] + \lambda_{\min}\left[1+2\sqrt{p_a(1-p_a)}\cos(\theta)\right]\}$

Note that the conditional LLRs satisfy $\mu = \sigma^2/2$, like their SISO equivalents. Another observation can be readily made. If $p_a = 1$, the means and variances of the conditional distributions of both bits are defined by the individual eigen values and the spatial channel reduces to an orthogonal matrix and a perfect eigen decomposition with two SISO channels.

Comments:

1. It is clear that to a good approximation the Gaussian means can be expressed in terms of the three parameters $\lambda_{\min}, \lambda_{\max}, p_a$, using the lower bounds, and hence it follows that MIB is also a function of these parameters, again to a good approximation. This can be shown to be the case under some conditions.
2. The following figure plots the conditional LLR PDFs of the two bits in BPSK with 2x2 SM.

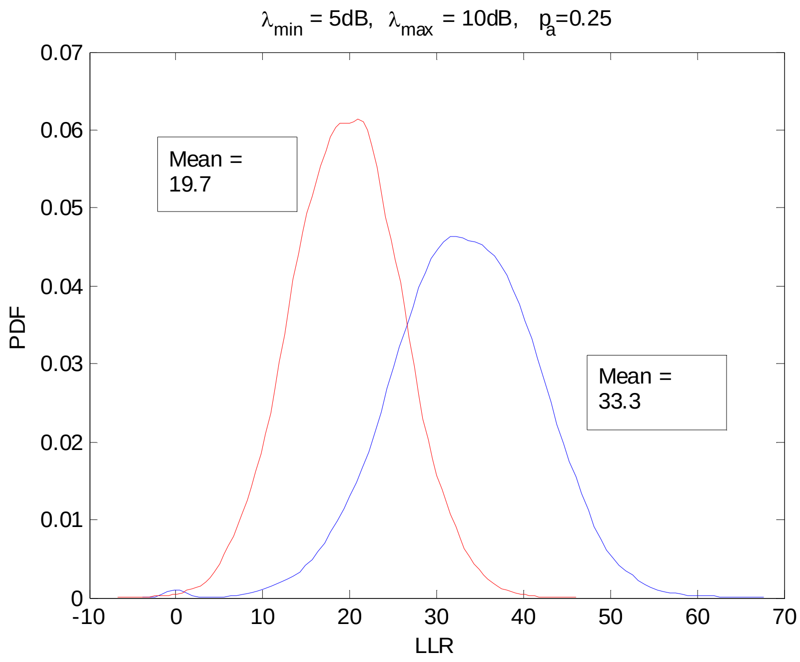


Figure 1 - Conditional LLR PDFs for a 2x2 BPSK System

The means are approximately equal to those calculated analytically

$$\lambda_{\min} p_a + \lambda_{\max}(1-p_a) = 19.6, \quad \lambda_{\max} p_a + \lambda_{\min}(1-p_a) = 33.5 \tag{1.17}$$

2) The above conditional means are obtained for BPSK. It can be easily shown that similar expressions are obtained for 16QAM and 64QAM. This follows noting that the minimum distance vectors for these modulations are given by $([\pm j \;\; \pm j],[\pm 1 \;\; \pm 1],[\pm j \;\; \pm 1],[\pm 1 \;\; \pm j],[\pm j, 0],...)$, constellations are Gray mapped and repeating the derivation for the Gaussian means above. We will skip these further details and focus on the numerical approximations that give good predictions.

Numerical Approximations for MIB Mapping

Three Parameter Interpolation

The mutual information function is evaluated numerically for uniformly spaced $\lambda_{\min}, \lambda_{\max}$ in the range [-10:2:40] dB and p_a with the range [0:0.1:0.5]. Given a set of the parameters in this range, several random channel matrix realizations are generated with these parameters and conditional LLR PDFs are obtained numerically with each of these matrix realizations. Mutual information is then computed by Monte-Carlo integration of conditional PDFs. ***For MIB mapping, the mutual information for a channel realization can be obtained by first computing the required three parameters of the channel matrix, and then linearly interpolating the numerically generated point-MI function.***

This approach can be difficult to implement in practice due to the large storage requirements. One approach is to reduce the number of interpolation points by using unequally spaced points depending on the variation of the MI function. A second alternative is to use good numerical approximations similar to SISO models. The later approach is outlined in the next section and results in fewer storage and computational requirements with acceptable penalty in performance prediction compared to this approach.

Identify Dominant Gaussians from the Channel Matrix

BPSK/QPSK

The three conditional LLR expressions derived in the previous section define the conditional PDFs of the two bits for BPSK. In their present form, they are hard to evaluate in an effective manner suited to practical implementation. However, we note that all the conditional distributions can be approximated as a mixture of Gaussian distributions. Following a similar approach to that in [1], we can then approximate the MIB by a sum of $J(.)$ functions. *A key difference is that the means of these distributions (and hence the variance and the statistics) can be expressed as functions of parameters derived from the channel matrix.* We propose following curve fit for the BPSK/QPSK mutual information in a 2x2 system.

Define

$$\begin{aligned}\vec{\boldsymbol{\gamma}} &= 4\times sort_{asc}\{\lambda_{\max} p_a + \lambda_{\min}(1-p_a), \lambda_{\min} p_a + \lambda_{\max}(1-p_a),\\ &\qquad \lambda_{\max}(1+2\sqrt{p_a(1-p_a)}\cos(\theta)) + \lambda_{\min}(1-2\sqrt{p_a(1-p_a)}\cos(\theta)),\\ &\qquad \lambda_{\max}(1-2\sqrt{p_a(1-p_a)}\cos(\theta)) + \lambda_{\min}(1+2\sqrt{p_a(1-p_a)}\cos(\theta))\}\\ &\approx 4\times sort_{asc}\{\lambda_{\max} p_a + \lambda_{\min}(1-p_a), \lambda_{\min} p_a + \lambda_{\max}(1-p_a),\\ &\qquad \lambda_{\max}(1-2\sqrt{p_a(1-p_a)}) + \lambda_{\min}(1+2\sqrt{p_a(1-p_a)})\}\end{aligned} \tag{1.18}$$

as the array with conditional means in ascending order. Note that the lower bound is used for the conditional means, since it is found to result in sufficient accuracy for all the modulations.

We treat/approximate a bitwise-conditional LLR PDF as the sum of the two most significant Gaussian distributions, which are defined by the smallest means. For QPSK, we have

$$I_2(\lambda_{\min}, \lambda_{\max}, P_a) = \frac{1}{2} J(a\sqrt{\boldsymbol{\gamma}(1)}) + \frac{1}{2} J(b\sqrt{\boldsymbol{\gamma}(2)}) \tag{1.19}$$

The optimal values from numerical simulations are given by

$$a = 0.85 \quad \mathrm{b} = 1.19 \tag{1.20}$$

To summarize, we have shown that the conditional LLR PDFs can be approximated as a mixture of Gaussian PDFs. While this is expected, we have explicitly derived these PDFs by expressing their means as a function of the eigen values and p_a - all real parameters that can be easily derived from channel matrix. For BPSK/QPSK two dominant Gaussian distributions can be considered to approximate the distribution and obtain a close curve fit to the 2x2 mutual information functions.

16QAM and 64QAM

We can obtain similar approximations for 16QAM and 64QAM. However an approximation which is valid at all SNRs and condition numbers is found to be inadequate in this case. Higher condition numbers are likely in 802.16e implementation (as high as $\kappa = 20dB$), and we have seen that the means of the Gaussian distributions constituting the LLR PDFs are dependent on SNR and condition number. With this observation, we propose approximations which are targeted to specific partitioned SNR and κ regions.
The 2x2 MI mapping is modeled as

$$I_m^{2x2}(\lambda_{\min}, \lambda_{\max}, p_a) = \frac{1}{3}\left(J(a_m\sqrt{\boldsymbol{\gamma}(1)} + J(b_m\sqrt{\boldsymbol{\gamma}(2)} + J(c_m\sqrt{\boldsymbol{\gamma}(3)}\right) \tag{1.21}$$

where $I_m^{2x2}(.)$ is the 2x2 SM MI function for modulation level m, γ is the vector of sorted means defined in(1.18), and a_m, b_m, c_m are the parameters which are evaluated for each SNR and κ partition. They are summarized in the tables below for 16 QAM and 64 QAM[2].

16 QAM	$1 < \kappa \le 10$	$10 < \kappa \le 100$	$\kappa > 100$
$-10dB < \lambda_{\min} < 8dB$	$a = 0.48,\ b = 0.27,\ c = 0.69$	$a = 0.40,\ b = 0.21,\ c = 0.56$	$a = 0.32,\ b = 0.13,\ c = 0.37$
$\lambda_{\min} > 8dB$	$a = 0.35,\ b = 0.43,\ c = 0.59$	$a = 0.37,\ b = 0.33,\ c = 100$	$a = 0.42,\ b = 0.11,\ c = 100$

Table 1 – Numerical Approximations to MMIB Mappings for 16 QAM, 2x2 SM, Vertical Encoding

64 QAM	$1 < \kappa \le 10$	$10 < \kappa \le 100$	$\kappa > 100$
$-10dB < \lambda_{\min} < 8dB$	$a = 0.23,\ b = 0.16,\ c = 0.59$	$a = 0.12,\ b = 0.12,\ c = 0.38$	$a = 0.08,\ b = 0.07,\ c = 0.17$
$\lambda_{\min} > 8dB$	$a = 0.20,\ b = 0.21,\ c = 0.62$	$a = 0.22,\ b = 0.13,\ c = 100$	$a = 0.24,\ b = 0.08,\ c = 100$

Table 2 - Numerical Approximations to MMIB Mappings for 64 QAM, 2x2 SM, Vertical Encoding

The MMIB of the channel realization is given by

$$M^{2x2} = \frac{1}{N}\sum_{i=1}^{N} I_m^{2x2}(\lambda_{\min}(\mathbf{H}_i), \lambda_{\max}(\mathbf{H}_i), p_a(\mathbf{H}_i)) \qquad (1.22)$$

where $\mathbf{H}_i$ is the 2x2 channel matrix on the i th subcarrier.

Computational Complexity

The expression (1.21) is similar to the SISO MIB mapping functions derived for 16QAM and 64QAM, with the only difference being that the parameters in the expression must be adapted to the SNR and condition number partition defined in the tables above.

BLER Mapping

The reference mapping (denoted by $B_\varphi(M)$) required to obtain BLER from the MMIB for SISO systems are obtained from AWGN performance results and numerically approximated in [1] using Gaussian cumulative model. In addition, the mappings were shown to be independent of the modulation scheme. The same mappings can be used as BLER mappings for the MIMO SM systems.

$$BLER = B_\varphi(M^{2x2}) \qquad (1.23)$$

Numerical Results

The plots below compare EESM with Eigen decomposition and MMIB with the above approach showing 15 different TU channel realizations. The spread of the blue curves represents the accuracy of the performance prediction.

[2] Though the conditional means are slightly different for these modulations compared to BPSK, the lower bounds on these means are similar.

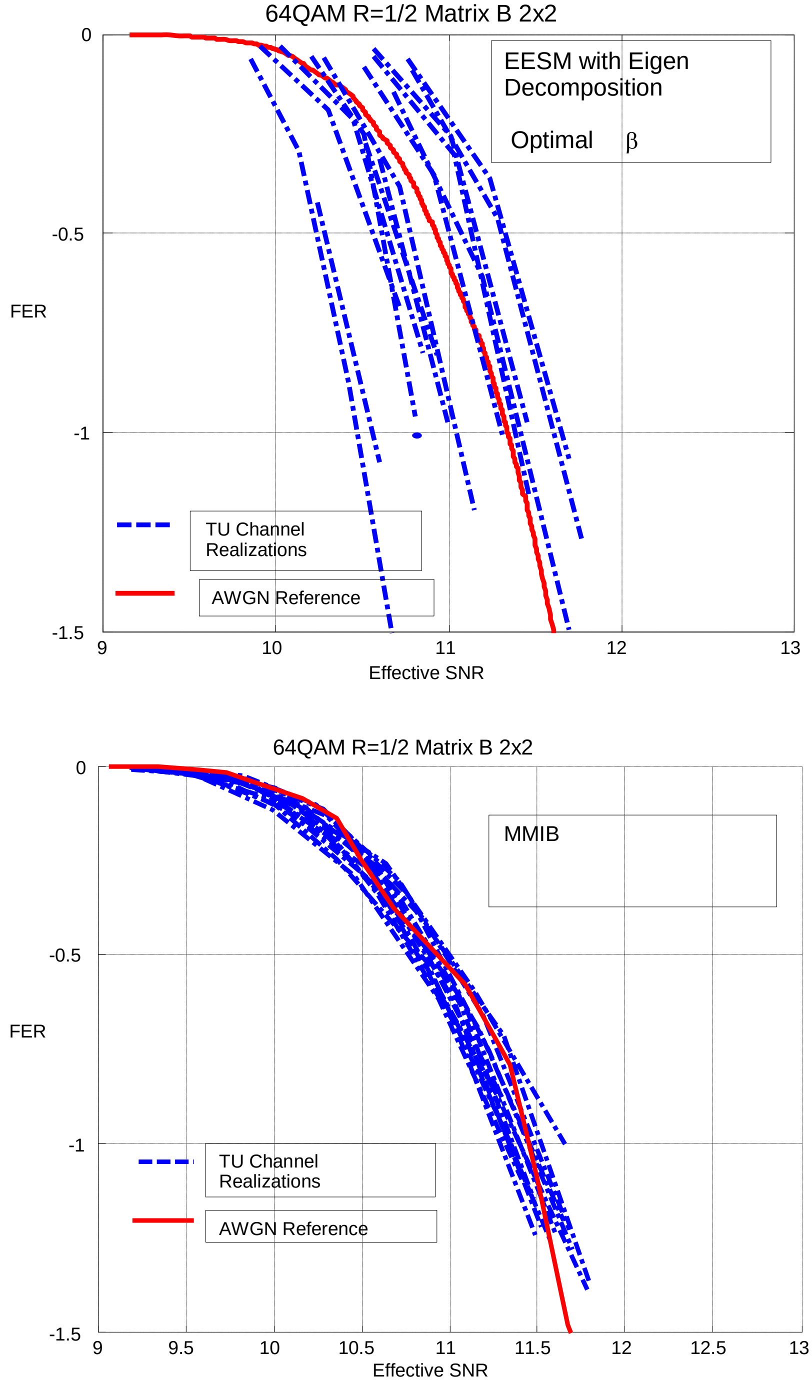
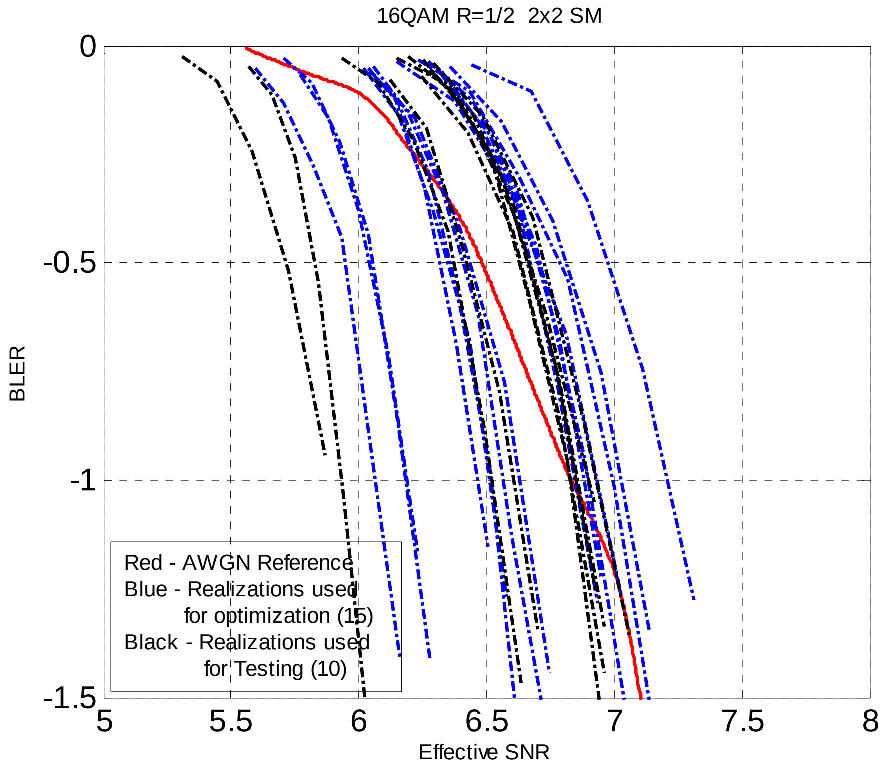


Figure 2 – Performance prediction for a MIMO ML receiver on a TU Uncorrelated MIMO Channel with a) EESM with Eigen decomposition b) MMIB for ML receivers

In this case, with EESM, the error in effective SNR evaluation is -1/+0.5 dB at 10% frame error rate. It is -0.2/+0.1 dB with the MMIB mappings. It is further noted that similar result is obtained with EESM when other mappings based on MMSE or SIC are used. It is clear using MMIB based mapping targeted at non-linear receiver operation results in significant improvement compared to EESM. Other SISO based mappings, are found to result in similar degradation. But the proposed approach is shown to have prediction accuracy similar to SISO, and with no additional beta parameters specific to MCSs (the functions once defined for each modulation, are common for all MCSs)

The result below shows the performance prediction of EESM and MMIB with a high correlation MIMO channel model [3]. The beta parameters used are optimized for high correlation channel model. It is clear that the performance prediction accuracy of EESM is not very good with a high correlation channel.



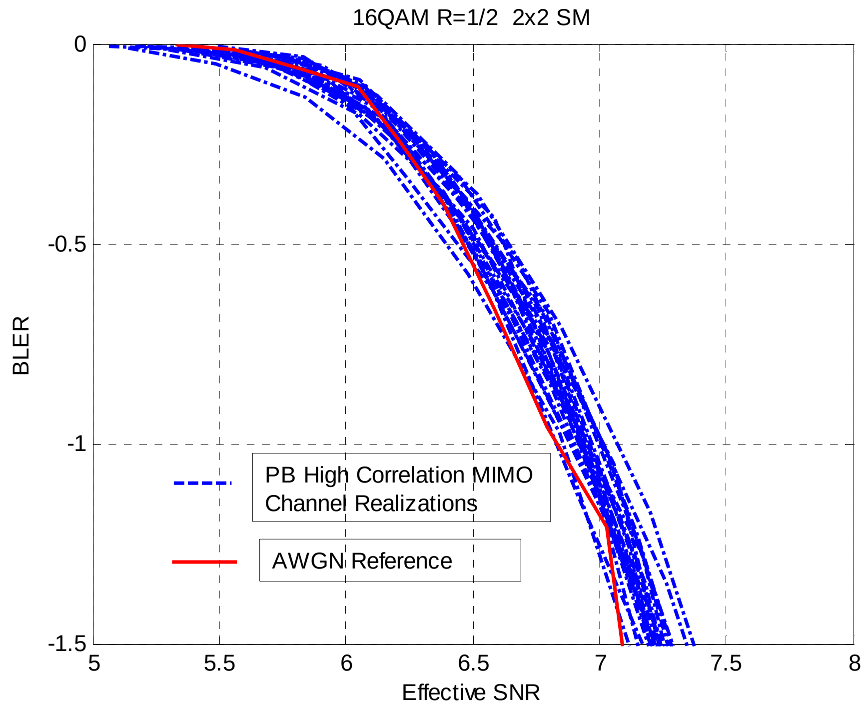


Figure 3 - Performance prediction for a MIMO ML receiver on a PB high Correlation MIMO channel with a) EESM with Eigen decomposition b) MMIB for ML receivers

Further, beta parameters are obtained for EESM by link simulations which typically assume particular MIMO channel model statistics. However, for MIMO ML receivers, we have seen that these beta parameters are sensitive to the link level channel model used.

Conclusions and Recommendation

This contribution summarizes the MMIB approach for ML receivers. Required numerical functions for MMIB evaluation of a 2x2 matrix channel are provided in this document. BLER mapping details are available in [1]. We recommend adopting MMIB approach over EESM for ML receivers.

EESM requires beta parameters to be synchronized in the document. Further these parameters are dependent on link level channel models used in the link simulation to optimize beta parameters. So, for accurate abstraction, different parameters may have to be used for different models. This may be sufficient for link level studies. However, in a system level simulation different users in a drop may experience different MIMO channel statistics. EESM cannot accurately model the performance in these cases. The additional simulation capability obtained by the channel models may be partially lost.

In addition, even with optimal parameterization, MMIB is shown to give significantly better performance prediction than EESM. This is primarily because this approach captures the performance of an ML receiver. Further, the slope of the MMIB to BLER curve for a specific channel realization closely matches that of the AWGN reference. This implies that EESM not only shows a fixed offset in prediction, but may also show additional jitter for a given channel realization, which may impact some system level results (Ex: Power control studies etc.,).

Proposed Text

Include Section 4.3.2.6: MIMO ML Receiver Abstraction

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4.3.2.6: MIMO ML Receiver Abstraction

MMIB can be evaluated for an ML receiver. In this section, we summarize the ML receiver abstraction to optimally compute MIB with the ML receiver using mixture Gaussian models for LLR PDFs. Details of the theoretical derivation can be found in [C80216m-07/xxx].

With vertical encoding, a codeword is transmitted on both the streams. In this case, for the purpose of code performance prediction, a single MIB metric is sufficient, which is the average MIB of the two streams. This section describes the computation of this metric for each modulation.

1) Obtain the Eigen value decomposition of the equivalent channel matrix

$$H^H H = VDV^H \qquad (1.24)$$

such that D is in the format

$$D = \begin{pmatrix} \lambda_{\max} & 0 \\ 0 & \lambda_{\min} \end{pmatrix} \qquad (1.25)$$

where

$$\begin{aligned} &\lambda_{\min} - \text{Minimum Eigen Value} \\ &\lambda_{\max} - \text{Maximum Eigen Value} \end{aligned} \qquad (1.26)$$

2) From the decomposition obtain the 3rd parameter

$$\begin{aligned} &p_a - \text{Eigen mode subspace power distribution} = \min\{p, 1-p\} \\ &\text{where } |\mathbf{V}|.|\mathbf{V}| = \begin{pmatrix} p & 1-p \\ 1-p & p \end{pmatrix},\ 0 \le p \le 1 \end{aligned} \qquad (1.27)$$

3) Obtain the following array of conditional means sorted in ascending order

$$\begin{aligned} \boldsymbol{\gamma} = sort_{asc}\{&\lambda_{\max} p_a + \lambda_{\min}(1-p_a), \lambda_{\min} p_a + \lambda_{\max}(1-p_a), \\ &\lambda_{\max}(1-2\sqrt{p_a(1-p_a)}) + \lambda_{\min}(1+2\sqrt{p_a(1-p_a)})\} \end{aligned} \qquad (1.28)$$

4)

i) For QPSK, the MMIB of the MIMO symbol is

$$I_2^{2x2}(\lambda_{\min}, \lambda_{\max}, P_a) = \frac{1}{2} J(a\sqrt{\boldsymbol{\gamma}(1)}) + \frac{1}{2} J(b\sqrt{\boldsymbol{\gamma}(2)}),\ a = 0.85, b = 1.19 \qquad (1.29)$$

where $I_m^{2x2}(.)$ is the 2x2 SM MI function for modulation level m.

ii)) For 16QAM and 64QAM, the 2x2 MI mapping is modelled as

$$I_m^{2x2}(\lambda_{\min}, \lambda_{\max}, p_a) = \frac{1}{3}\left(J(a_m\sqrt{\gamma(1)} + J(b_m\sqrt{\gamma(2)} + J(c_m\sqrt{\gamma(3)} \right) \quad (1.30)$$

where a_m, b_m, c_m are the parameters which are listed in the following tables for each SNR and condition number($\kappa = \lambda_{\max} / \lambda_{\min}$) partition.

16 QAM	$1 < \kappa \le 10$	$10 < \kappa \le 100$	$\kappa > 100$
$-10dB < \lambda_{\min} < 8dB$	$a = 0.48,\ b = 0.27$ $c = 0.69$	$a = 0.40,\ b = 0.21$ $c = 0.56$	$a = 0.32,\ b = 0.13$ $c = 0.37$
$\lambda_{\min} > 8dB$	$a = 0.35,\ b = 0.43$ $c = 0.59$	$a = 0.37,\ b = 0.33$ $c = 100$	$a = 0.42,\ b = 0.11$ $c = 100$

Table 3 – Numerical Approximation Parameters for 16 QAM, 2x2 SM

64 QAM	$1 < \kappa \le 10$	$10 < \kappa \le 100$	$\kappa > 100$
$-10dB < \lambda_{\min} < 8dB$	$a = 0.23,\ b = 0.16$ $c = 0.59$	$a = 0.12,\ b = 0.12$ $c = 0.38$	$a = 0.08,\ b = 0.07$ $c = 0.17$
$\lambda_{\min} > 8dB$	$a = 0.20,\ b = 0.21$ $c = 0.62$	$a = 0.22,\ b = 0.13$ $c = 100$	$a = 0.24,\ b = 0.08$ $c = 100$

Table 4 - Numerical Approximation Parameters for 64 QAM, 2x2 SM

The MMIB of the channel realization is given by

$$M^{2x2} = \frac{1}{N}\sum_{i=1}^{N} I_m^{2x2}(\lambda_{\min}(\mathbf{H}_i), \lambda_{\max}(\mathbf{H}_i), p_a(\mathbf{H}_i)) \quad (1.31)$$

where $\mathbf{H}_i$ is the $n_R \times 2$ channel matrix on the i th subcarrier.

The MMIB to BLER mapping is similar to that of SISO as in section 4.3.2.4. The code size should correspond to the total codeword size on the two streams.

----- *End Proposed Text* ---

References

[1] IEEE C80216m-07/097, "Link Performance Abstraction based on Mean Mutual Information per Bit (MMIB) of the LLR Channel", IEEE 802.16 TGm contribution, May 04, 2007.

[2] IEEE Std 802.16 – 2004, "IEEE Standard for Metropolitan Area Networks - Part 16: Air Interface for Fixed Broadband Wireless Systems"

[3] MIMO Channel Models for MTG RCT, v16a, Technical Working Group, WiMAX Forum.