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Abstract: This document is a complement to deliverable D4.2. The objective is the design of practical algorithms for FBMC, exploiting the maximum likelihood principle for the contexts of MIMO 2x2 and MIMO 4x4, and for binary and multi-bit data.
The corresponding software is delivered to WP9, for system simulation and implementation, complexity evaluation, and comparison with OFDM.

Contents

1 Introduction

In filter bank multicarrier (FBMC) transmission, maximum speed is reached when offset quadrature amplitude modulation (OQAM) is employed. This is different from quadrature amplitude modulation (QAM), where the real part and the imaginary part of the data symbol are transmitted jointly and simultaneously. With OQAM, the real part and the imaginary part of the data symbol are emitted separately and independently, just as in pulse amplitude modulation (PAM). From the MIMO perspective, this difference has two main consequences when maximum likelihood (ML) techniques are envisaged

a) the computational complexity of the algorithms is based on powers of two in OQAM, while it is based on powers of four in QAM. Therefore, multibit algorithms are more practical in OQAM than in QAM,
b) for a given signal-to-noise ratio (SNR) at the receiver input, the theoretical equivalent SNR which determines the bit error rate (BER) of the ML algorithm is greater with OQAM, which leads to a smaller BER.

In short, OQAM modulation has the potential to outperform QAM modulation, with a reduced computational complexity.
However, there is an obstacle for OQAM to realize its potential, it is the interference term which accompanies every real data symbol. In fact, most of the effort in developing ML algorithms for OQAM is related to the estimation and the cancellation of this interference term.
In the present document, algorithms are developed for the MIMO 2x2 and MIMO 4x4 cases and they exploit either MMSE estimations of the interference terms or partial reconstitution of these terms from estimated present and future data and decided past data. But, first, the OQAM-QAM comparison in the ML context is carried out for the case of MIMO 2x2 and binary data, that is binary phase shift keying (BPSK) modulation and quaternary phase shift keying (QPSK) modulation respectively.

2 Performance of ML algorithms

Considering a system with 2 transmit antennas and 2 receive antennas, the received signals are expressed by

$$x_1 = h_{11}s_1 + h_{12}s_2 + b_1 \quad ; \quad x_2 = h_{21}s_1 + h_{22}s_2 + b_2 \tag{1}$$

where s_1 , s_2 , b_1 , b_2 designate the data symbols and the noise terms respectively. The complex values h_{11} , h_{12} , h_{21} , h_{22} represent the MIMO channel matrix elements.
If the modulation is BPSK, then $s_1 = d_1$ and $s_2 = d_2$, where d_1 and d_2 are the real data symbols ±1. With QPSK (or QAM 4), $s_1 = d_{1r} + j\,d_{1i}$ and $s_2 = d_{2r} + j\,d_{2i}$, and $d_{1,2r,i} = \pm 1$.
The maximum likelihood technique consists, in a first step, of computing the error function

$$E_r = \left|x_1 - h_{11}s_1 - h_{12}s_2\right|^2 + \left|x_2 - h_{21}s_1 - h_{22}s_2\right|^2 \tag{2}$$

for all possible values of the data symbols [1]. The channel matrix elements are assumed to be known.

2.1 BPSK modulation

Two signals are emitted and two real data symbols are involved, which leads to $2^2 = 4$ error function calculations. When the data symbols used in the calculation are those that have been emitted, the error function is

$$E_0 = |b_1|^2 + |b_2|^2 \tag{3}$$

Now, if the emitted symbol is $d_1 = 1$ and -1 is used in the calculation instead, the error function takes on the value

$$E_1 = |2h_{11} + b_1|^2 + |2h_{21} + b_2|^2 \tag{4}$$

At the output of the ML decoder, the decoded symbols are those which minimize the error function. Thus, E_0 and E_1 must be compared and taking their difference leads to

$$\frac{E_1 - E_0}{4} = |h_{11}|^2 + |h_{21}|^2 + \mathrm{Re}\{h_{11}^* b_1 + h_{21}^* b_2\} \tag{5}$$

The noise samples $b_1 = b_{1r} + j\,b_{1i}$ and $b_2 = b_{2r} + j\,b_{2i}$ are assumed to be made each of two independent Gaussian variables of power σ^2 each.

At the decision point, the signal-to-noise ratio, derived from (5), is

$$SNR_{d1} = \frac{|h_{11}|^2 + |h_{21}|^2}{\sigma^2} \tag{6}$$

Similarly, writing the equivalent of equation (5) for d_2 false yields

$$SNR_{d2} = \frac{|h_{12}|^2 + |h_{22}|^2}{\sigma^2} \tag{7}$$

And for both data symbols false, taking into account the sign of the errors

$$SNR_{d1,2} = \frac{|h_{11} \pm h_{12}|^2 + |h_{21} \pm h_{22}|^2}{\sigma^2} \tag{8}$$

The bit error rate is mainly derived from these SNR values. It is worth pointing out that, through expression (8), the bit error rate is dependent on the relative phases of the channel elements h_{11} and h_{12} on one hand, and h_{21} and h_{22} on the other hand.

2.2 QPSK modulation

Again, two signals are emitted but, now, 4 data symbols are involved, which leads to $4^2 = 16$ error function calculations. When the data symbols used in the error function calculation are correct, the value obtained is E_0 as above. Then, if d_{1r} is false, the error function calculated as above leads to the difference

$$\frac{E_{d1r} - E_0}{4} = |h_{11}|^2 + |h_{21}|^2 + \mathrm{Re}\{h_{11}^* b_1 + h_{21}^* b_2\} \tag{9}$$

Next, if d_{1i} is false, the difference is

$$\frac{E_{d1i} - E_0}{4} = |h_{11}|^2 + |h_{21}|^2 + \mathrm{Im}\{h_{11}^* b_1 + h_{21}^* b_2\} \tag{10}$$

and for d_{1r} and d_{1i} false

$$\frac{E_{d1r,i} - E_0}{4} = 2\left(|h_{11}|^2 + |h_{21}|^2\right) + \mathrm{Re}\{h_{11}^* b_1 + h_{21}^* b_2\} + \mathrm{Im}\{h_{11}^* b_1 + h_{21}^* b_2\} \tag{11}$$

At this stage, there is no difference between BPSK and QPSK, because the SNR expressions derived from (9-10) are the same as (6). In fact, the difference comes from the

double errors, on two different symbols. The 4 possible combinations lead to the following SNR values

$$SNR_{d1r,2r} = \frac{\left|h_{11} \pm h_{12}\right|^2 + \left|h_{21} \pm h_{22}\right|^2}{\sigma^2} \quad ; \quad SNR_{d1r,2i} = \frac{\left|h_{11} \pm j\,h_{12}\right|^2 + \left|h_{21} \pm j\,h_{22}\right|^2}{\sigma^2} \qquad (12)$$

$$SNR_{d1i,2r} = \frac{\left|j\,h_{11} \pm h_{12}\right|^2 + \left|j\,h_{21} \pm h_{22}\right|^2}{\sigma^2} \quad ; \quad SNR_{d1i,2i} = \frac{\left|h_{11} \pm h_{12}\right|^2 + \left|h_{21} \pm h_{22}\right|^2}{\sigma^2}$$

When they are compared to expression (8) for double errors in BPSK, these expressions reveal that the 4 phases, namely 1, j, -1, -j, are involved in the summations of the channel matrix elements, instead of the 2 phases, 1 and -1. Thus, double errors in QPSK lead to SNR values which are smaller than the SNR values for BPSK or equal. In a random context for the transmission channel, the difference in the probability of error can be calculated. Finally, the BER in OQAM is smaller than the BER in QAM. A detailed analysis is provided in reference [2] for flat fading channels.

An illustration is given by the curves shown in Fig.1, where a flat Rayleigh fading channel is used. The difference in performance is about 1 dB.

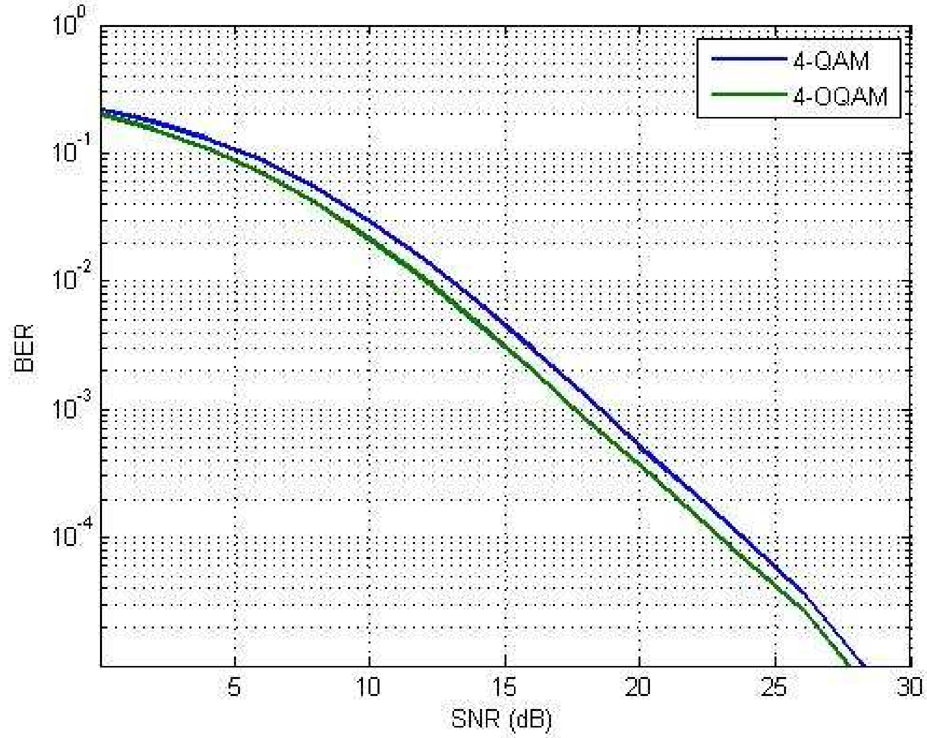

Fig.1. Performance of OQAM and QAM modulations for MIMO 2x2 and ML

3 Algorithms for MIMO 2x2 based on MMSE estimation

When the channel matrix elements and the additive noise power are available, the minimum mean square error (MMSE) technique can be invoked to obtain an estimation of the OQAM interference terms [3]. Then, the ML technique can be applied.

3.1 FBMC and MIMO-MMSE

When the transmitter and the receiver of an FBMC system are connected back to back, the signal at the receiver output, in sub-channel "i" at time "n" is expressed by

$$x_i(n) = d_i(n) + ju_i(n) \tag{13}$$

where $d_i(n)$ is a data symbol and $u_i(n)$ is an interference term expressed by

$$u_i(n) = \sum_{l=-1}^{1} \sum_{k=-(2K-1)}^{2K-1} c_{lk} d_{i+l}(n-k) \quad ; \quad k,l \neq 0 \tag{14}$$

The coefficients c_{lk} represent the system impulse response and K is the overlapping factor of the prototype filter. For $K = 4$, the main coefficients are given in Table 1.
With binary data, the interference term $u_i(n)$ takes on values in a large discrete set in the range [-3,+3] and this is an issue for maximum likelihood (ML) detection, because it is not realistic to consider all its possible values. Thus, this term has to be evaluated, before the ML technique is applied, and, in a first approach, MMSE is used to that purpose.

time s.c.	n-2	n-1	n	n+1	n+2	n+3
i-1	-0.125	- j 0.206	0.239	j 0.206	-0.125	-j 0.043
i	0	0.564	**1**	0.564	0	-0.067
i+1	-0.125	j 0.206	0.239	-j 0.206	-0.125	j 0.043

Table 1. System impulse response (main part)

Among the spatial multiplexing schemes, MIMO 2x2 is the simplest and most widely used scheme. Therefore, to begin with, the detection techniques are developed in that context, where the system has two transmit antennas and two receive antennas. At a particular time, in a particular sub-channel, the following signals are received

$$\begin{aligned} x_1 &= h_{11}(d_1 + ju_1) + h_{12}(d_2 + ju_2) + b_1 \\ x_2 &= h_{21}(d_1 + ju_1) + h_{22}(d_2 + ju_2) + b_2 \end{aligned} \tag{15}$$

where d, u, b designate, respectively, the data symbols, the OQAM interference terms and the noise terms. The complex scalars h_{11}, h_{12}, h_{21} and h_{22} represent the MIMO transmission channel elements at the center frequency of the sub-channel under consideration, assuming perfect frequency and time synchronization after sub-channel equalization.

In matrix form, equations (15) are rewritten as

$$X = HS + B \tag{16}$$

The MMSE technique consists of finding the matrix G which minimizes the cost function

$$J = E[|s_1 - g_{11}x_1 - g_{12}x_2|^2 + |s_2 - g_{21}x_1 - g_{22}x_2|^2] \tag{17}$$

Assuming that the source signals $s_1 = d_1 + ju_1$ and $s_2 = d_2 + ju_2$ are statistically independent, the solution is

$$G^t = (H^* H^t + \sigma^2 I_2)^{-1} H^* \tag{18}$$

where H^t is the transpose of H and H^* is the conjugate. The noise power is σ^2. In the absence of noise, $G = H^{-1}$, which is the solution of the so-called "zero forcing" criterion. Accordingly, the "zero forcing" estimation of the source signals is

$$\tilde{S} = S + H^{-1}B \tag{19}$$

As concerns the MMSE estimation, it takes a more complicated form and the 2 elements of the vector are

$$\tilde{s}_1 = \frac{\left(|D|^2 + \sigma^2(|h_{11}|^2 + |h_{21}|^2)\right)s_1 + \sigma^2 A s_2 + \left(h_{11}^*\sigma^2 + D^* h_{22}\right)b_1 + \left(h_{21}^*\sigma^2 - D^* h_{12}\right)b_2}{\sigma^2(|h_{11}|^2 + |h_{21}|^2 + |h_{12}|^2 + |h_{22}|^2) + |D|^2 + \sigma^4} \quad (20)$$

and

$$\tilde{s}_2 = \frac{\left(|D|^2 + \sigma^2(|h_{22}|^2 + |h_{12}|^2)\right)s_2 + \sigma^2 A^* s_1 + \left(h_{12}^*\sigma^2 - D^* h_{21}\right)b_1 + \left(h_{22}^*\sigma^2 + D^* h_{11}\right)b_2}{\sigma^2(|h_{11}|^2 + |h_{21}|^2 + |h_{12}|^2 + |h_{22}|^2) + |D|^2 + \sigma^4} \quad (21)$$

with $D = \det(H)$ and $A = h_{11}^* h_{12} + h_{21}^* h_{22}$. The signal-to-noise ratio associated with MMSE, for the decision on d_1, is given by

$$SNR_1 = \frac{\left(|D|^2 + \sigma^2(|h_{11}|^2 + |h_{21}|^2)\right)^2}{\sigma^4 |A|^2 + \left[\left|h_{11}^*\sigma^2 + D^* h_{22}\right|^2 + \left|h_{21}^*\sigma^2 - D^* h_{12}\right|^2\right]\sigma_b^2} \quad (22)$$

and for the decision on d_2 it is

$$SNR_2 = \frac{\left(|D|^2 + \sigma^2(|h_{12}|^2 + |h_{22}|^2)\right)^2}{\sigma^4 |A|^2 + \left[\left|h_{12}^*\sigma^2 + D^* h_{21}\right|^2 + \left|h_{22}^*\sigma^2 - D^* h_{11}\right|^2\right]\sigma_b^2} \quad (23)$$

The “zero forcing” estimation has no bias, but the MMSE estimation yields higher signal-to-noise ratios.

3.2 Combining MMSE and ML – binary data case

As mentioned in the previous section, the maximum likelihood principle, when the data symbols d_1 and d_2 are searched, implies the calculation of the error function

$$E_r = \left|x_1 - h_{11}d_1 - h_{12}d_2\right|^2 + \left|x_2 - h_{21}d_1 - h_{22}d_2\right|^2 \quad (24)$$

for all possible values of the data symbols. Assuming binary data, $d_1 = \pm 1$ and $d_2 = \pm 1$, 4 evaluations are needed. Then, the minimum of the error function values is picked and the data set which is involved in it is the output of the ML detector.

In order to assess the error rate, it is necessary to evaluate the probability that an error function value with the wrong data be smaller than the error function with the correct data, denoted E_0. If E_1 is associated with a wrong d_1, -1 instead of 1, the difference with E_0 is expressed by

$$\frac{E_1 - E_0}{4} = \left|h_{11}\right|^2 + \left|h_{21}\right|^2 + u_2 \,\mathrm{Im}\left\{h_{11}h_{12}^* + h_{21}h_{22}^*\right\} + \mathrm{Re}\left\{h_{11}b_1^* + h_{21}b_2^*\right\} \quad (25)$$

The corresponding signal-to-noise ratio is, considering now the sign of the error,

$$SNR_{d1} = \frac{\left[\left|h_{11}\right|^2 + \left|h_{21}\right|^2 \pm u_2 \,\mathrm{Im}(h_{11}h_{12}^* + h_{21}h_{22}^*)\right]^2}{(\left|h_{11}\right|^2 + \left|h_{21}\right|^2)\sigma^2 / 2} \quad (26)$$

Similarly for a wrong d_2

$$SNR_{d2} = \frac{\left[\left|h_{22}\right|^2 + \left|h_{12}\right|^2 \pm u_1 \,\mathrm{Im}(h_{11}h_{12}^* + h_{21}h_{22}^*)\right]^2}{(\left|h_{22}\right|^2 + \left|h_{12}\right|^2)\sigma^2 / 2} \quad (27)$$

Finally, for wrong d_1 and d_2

$$SNR_{d1,d2} = \frac{\left[|h_{11} \pm h_{12}|^2 + |h_{21} \pm h_{22}|^2 \pm (u_1 \pm u_2)\,\mathrm{Im}(h_{11}h_{12}^* + h_{21}h_{22}^*)\right]^2}{(|h_{11} \pm h_{12}|^2 + |h_{21} \pm h_{22}|^2)\sigma^2 / 2} \tag{28}$$

It is remarkable to observe that SNR_{d1} depends on u_2, while SNR_{d2} depends on u_1. Finally, from the above expressions and the connection between signal-to-noise ratio and bit error rate (BER), it appears that the performance of the ML scheme, in terms of BER, is impacted by the interference terms and the impact is proportional to the quantity $\mathrm{Im}(h_{11}h_{12}^* + h_{21}h_{22}^*)$ which is known, while u_1 and u_2 are unknown. Now, if estimated values $\tilde{u}_1$ and $\tilde{u}_2$ are available and if they are introduced into the error function (24), equation (25) becomes

$$\frac{E_1 - E_0}{4} = |h_{11}|^2 + |h_{21}|^2 + \Delta u_2\,\mathrm{Im}\left\{h_{11}h_{12}^* + h_{21}h_{22}^*\right\} + \mathrm{Re}\left\{h_{11}b_1^* + h_{21}b_2^*\right\} \tag{29}$$

with $\Delta u_2 = u_2 - \tilde{u}_2$.

A first approach consists of taking the estimations $\tilde{u}_1$ and $\tilde{u}_2$ of the MMSE technique described above. Then, the issue is to assess the performance of the MMSE-ML method, with respect to MMSE only and with respect to the optimal decoding, which corresponds to $\Delta u_{1,2} = 0$. For simplicity reasons, the analysis is carried out with the "zero-forcing" estimation, conjecturing that the MMSE estimation leads to similar results.

In the zero-forcing (ZF) technique, the inverse channel matrix is used to estimate the interference terms. According to equation (19), the estimation error is given by

$$\begin{bmatrix} \Delta u_1 \\ \Delta u_2 \end{bmatrix} = \mathrm{Im}\left\{ \frac{1}{h_{11}h_{22} - h_{21}h_{12}} \begin{bmatrix} h_{22} & -h_{12} \\ -h_{21} & h_{11} \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \right\} \tag{30}$$

Then, under the assumption of weak correlation between the noise terms in (29) and the above estimation errors for the interference terms, the signal-to-noise ratio SNR_{d1} can be expressed by

$$SNR_{d1} = \frac{|h_{11}|^2 + |h_{21}|^2}{\frac{\sigma^2}{2}(1 + A)} \tag{31}$$

with

$$A = \frac{(\mathrm{Im}\left\{h_{11}h_{12}^* + h_{21}h_{22}^*\right\})^2}{|h_{11}h_{22} - h_{21}h_{12}|^2} \tag{32}$$

The signal-to-noise ratio associated with zero forcing, for the decision on d_1, is given by

$$SNR_{ZF} = \frac{1}{\frac{|h_{22}|^2 + |h_{12}|^2}{|h_{11}h_{22} - h_{12}h_{21}|^2}\sigma^2 / 2} \tag{33}$$

where σ^2 is the noise power, as explained in section 2. Combining equations (31-33), the gain of using the ZF-ML combination with respect to ZF alone is given by

$$G_{ZF-ML} = \frac{(|h_{11}|^2 + |h_{21}|^2)(|h_{22}|^2 + |h_{12}|^2)}{|h_{11}h_{22} - h_{12}h_{21}|^2 + (\mathrm{Im}\{h_{11}h_{12}^* + h_{21}h_{22}^*\})^2} \tag{34}$$

The magnitude of this gain depends on the elements of the channel matrix. Optimal detection is achieved if $\mathrm{Im}\{h_{11}h_{12}^* + h_{21}h_{22}^*\} = 0$. For example, with

$$h_{11} = 1; h_{22} = j; h_{12} = 0.7 + 0.7j; h_{21} = -0.7 + 0.7j$$

the gain is $G_{ZF-ML} = 2$ (3 dB), while if $h_{21} = 0.7 - 0.7j$ the gain is unity (0 dB). In the presence of a varying channel, the gain is averaged over the realizations.

An illustration of the performance of the MMSE-ML method is provided by the curves shown in Fig.2. Flat Rayleigh fading channels are used in the simulation with binary data and the FBMC system has 512 sub-channels. The bit error rate is given as a function of the SNR at the decoder input. The optimal detection curve corresponds to known OQAM interference terms.

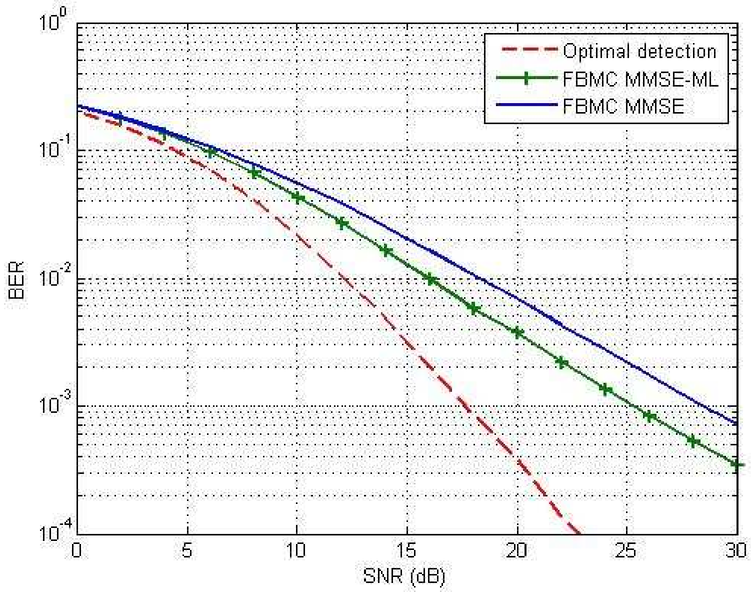

Fig.2. Performance of the MMSE-ML scheme for binary data

A significant gain is obtained by the MMSE-ML combination, with respect to MMSE, but the performance is still far from the optimum. At $BER = 10^{-2}$, the curves of Fig.2 show that the gain of MMSE-ML with respect to MMSE is 2 dB.

3.3 Simulation results for multi-bit data

The analysis which has been carried out for binary data can be extended to multi-bit data. Then, in the error function calculations, the factor 2 is replaced by a factor which can take on several values.

The curves obtained for 2 bit data are shown in Fig.3. The corresponding modulation is called OQAM-16, with reference to the QAM terminology. For data with 3 bits, OQAM-64, the curves are given in Fig.4. It can be observed that the improvement of the MMSE-ML combination over pure MMSE diminishes when the order of the modulation increases.

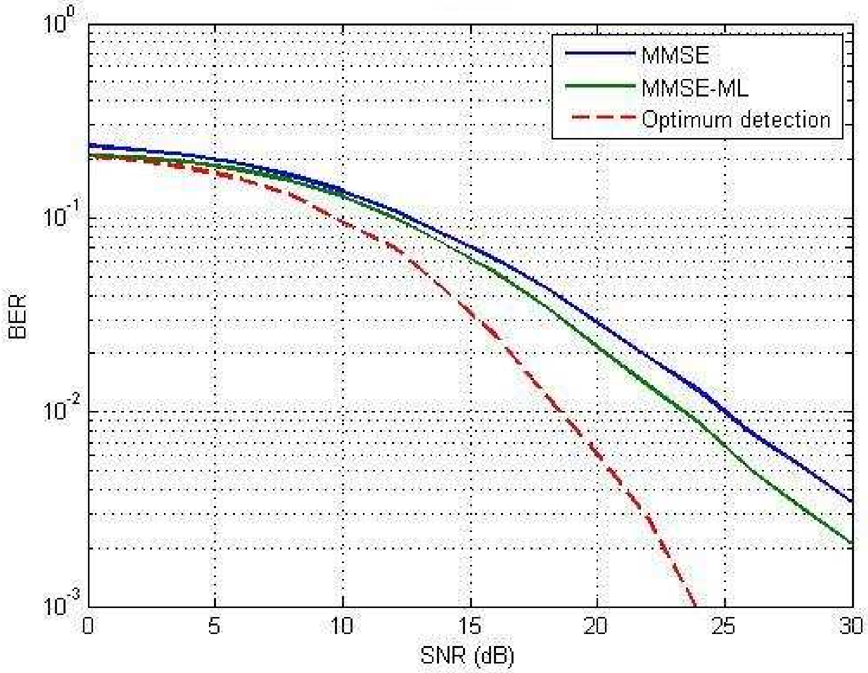

Fig.3. Performance of the MMSE-ML scheme for 2 bit data (OQAM-16)

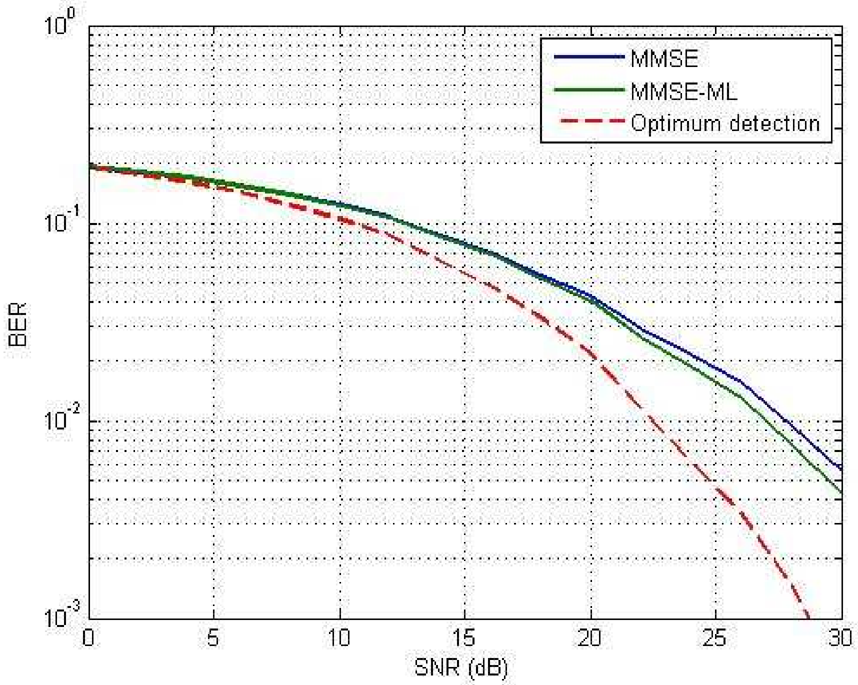

Fig.4. Performance of the MMSE-ML scheme for 3 bit data (OQAM-64)

It is worth pointing out that no additional delay is introduced in the MMSE-ML decoding process, which is an important aspect for some applications.

4 Algorithms with calculation of the interference term

Optimal detection requires perfect estimation of the interference terms and equation (14) is invoked. Therefore, the data symbols involved in equation (14) must be available. These data symbols can be estimated by the above proposed MMSE-ML technique, but an additional delay of K- 1 multicarrier symbols is introduced in the transmission. The delay might be critical and, in order to limit its value, it is interesting to use a small set of coefficients of the system impulse response. Of course, if an incomplete impulse response is exploited, a residual interference term remains, which introduces a floor in the BER versus received SNR curve.
Three neighborhoods to the central unity term in Table 1 are considered, with 8, 12 and 18 coefficients respectively. For each of these neighborhoods, a rough assessment of the performance can be derived from the maximum value of the interference term deviation, $\Delta u_{\max}$, which is calculated. The results are given in Table 2, and the corresponding additional delays are indicated.

Neighborhood	Δu_{max}	delay
1	0.84	1
2	0.34	2
3	0.03	3

Table 2. Maximum deviation of the interference term calculated with 3 sets of coefficients.

Then, using equations similar to (26-28), the performance can be assessed in each of the 3 cases. Clearly, neighborhood 1 is likely to produce a high bit error rate, while neighborhood 3 should be close to optimum, except for high SNR values.

In order to optimize the approach, it is beneficial to include into the interference calculation the data symbols which have already been decided and limit the MMSE-ML estimation to future symbols. Since previous decisions are used in the process, the scheme is denominated Recursive-ML (Rec-ML). The corresponding block diagram is shown in Fig.5.

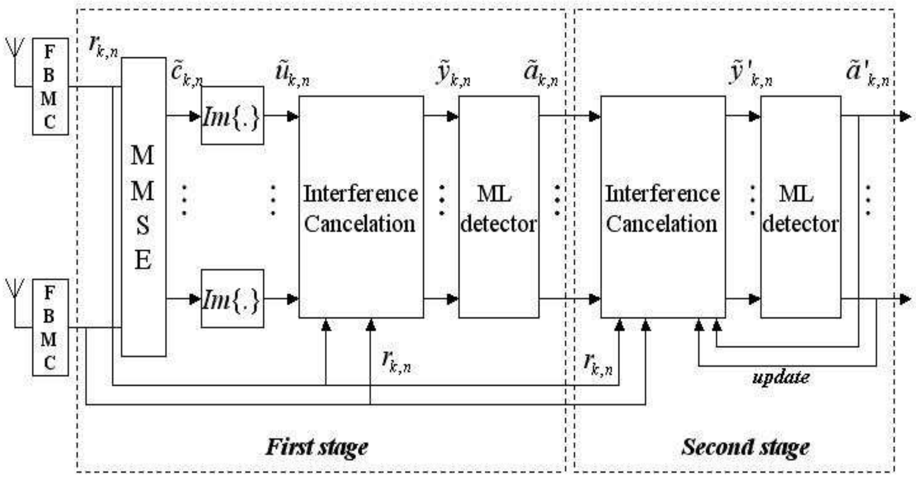

Fig.5. The 2 stages of the ML scheme with interference calculation

The first stage represents the MMSE-ML scheme, with the estimation of the interference term and its cancellation in the ML process. The second stage exploits the results of the first stage

and the previous outputs, it includes the additional delay incurred by the approach. Of course, decision errors on data symbols impact the performance of the scheme.

The direct calculation of the interference term with binary data, or OQAM-4 modulation, leads to the results shown in Fig.6. As expected, neighborhood 1 (8 coefficients) produces a high BER floor due to the high value of the residual interference. There is virtually no difference between neighborhoods 2 and 3 as long as the SNR at the receiver output does not exceed 20 dB. This means that the contribution of the residual interference is negligible, compared to the noise level. Therefore, neighborhood 2 is a satisfactory compromise between performance and delay.

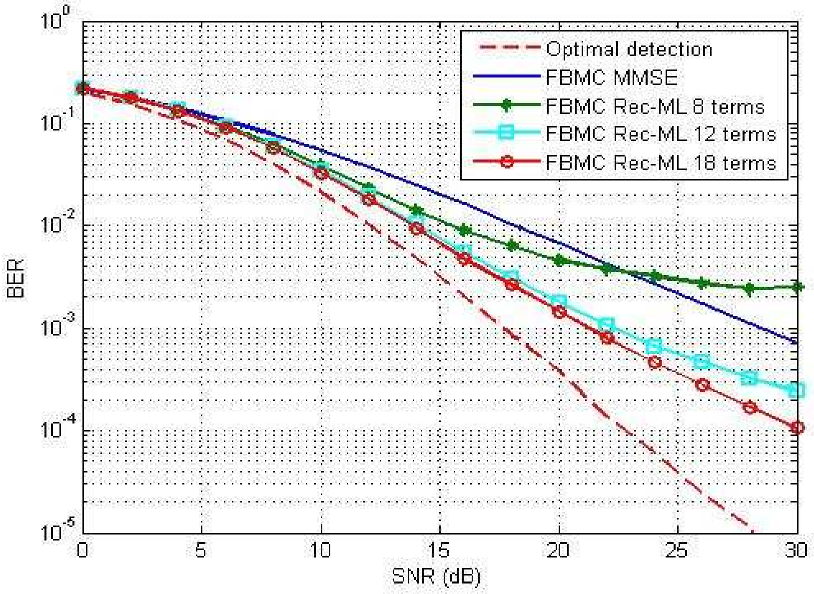

Fig.6. Performance of the recursive-ML scheme for binary data

The results obtained with 2-bit data, or OQAM-16, are shown in Fig.7. With the increase in SNR needed in that context, the BER floor effect is more important and neighborhood 3 with 18 coefficients is preferable.

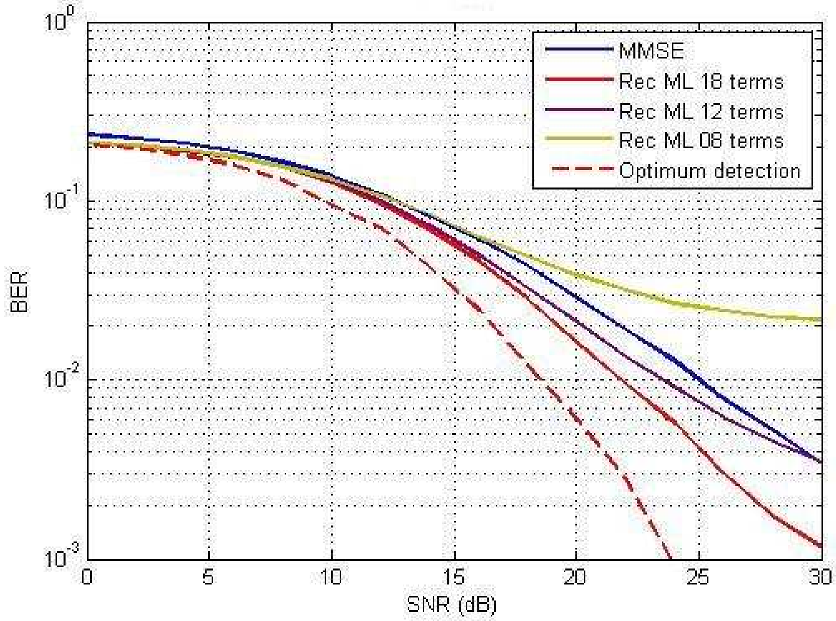

Fig.7. Performance of the recursive-ML scheme for 2-bit data (OQAM-16)

Now, even for the most complete neighborhood employed in the interference term calculation, there is still a gap with respect to optimal detection, which stems from the decision and estimation errors on the data symbols involved in the calculation. This gap can be reduced if error correction is introduced in the detection loop as proposed in [4], but at the cost of more delay.

5. Algorithms for MIMO 4x4

The schemes presented for MIMO 2x2 in the previous section, and their analysis can be extended to the MIMO 4x4 configuration, with the corresponding increase in computational complexity. The received signal vector used for ML decoding is expressed by

$$X = HD + j\,H\Delta U + B \tag{35}$$

where D is the 4-element data vector and ΔU is the estimation error of the interference terms. When the correct data are used in the error function calculation, the value is

$$E_0 = \left| j\,H\Delta U + B \right|^2 \tag{36}$$

Next, the following notations are considered for the 4x4 channel matrix and the estimation of the interference terms

$$H = [V_1\ V_2\ V_3\ V_4\ ]\ \ ;\ \ \Delta U^t = [\Delta u_1\ \Delta u_2\ \Delta u_3\ \Delta u_4\ ] \tag{37}$$

Denoting by E_{di} the error function when the wrong value of the data symbol d_i is used in the calculation, the difference is given by

$$\frac{E_{di} - E_0}{4} = V_i V_i^* + \mathrm{Im}\left\{ V_i^t \sum_{\substack{k=1\\k\neq i}}^{4} V_k^* \Delta u_k \right\} + \mathrm{Re}\left\{ V_i^t B^* \right\} \tag{38}$$

This is the extension to dimension 4 of equation (29) for dimension 2. Again, the performance of the combination MMSE-ML depends on the elements of the channel matrix and optimal decoding is reached if

$$\mathrm{Im}\left\{ V_i^t \sum_{\substack{k=1\\k\neq i}}^{4} V_k^* \Delta u_k \right\} = 0 \tag{39}$$

Then, the gain brought by the MMSE-ML scheme in the case MIMO 4x4 should be similar to the gain obtained in the case MIMO 2x2 and confirmation is provided by the curves shown in Fig.8, for binary data. In fact, the gain obtained with respect to MMSE is about 3 dB at $BER = 10^{-2}$.

Although more complex, the algorithms based on the calculation of the interference terms can be applied to MIMO 4x4. The performance obtained for the recursive-ML scheme is illustrated in Fig.9. The curves show that the BER floor effect is smaller for MIMO 4x4 than for MIMO 2x2. It is worth pointing out that neighborhood 2 leads to virtually the same performance as neighborhood 3 in that case.

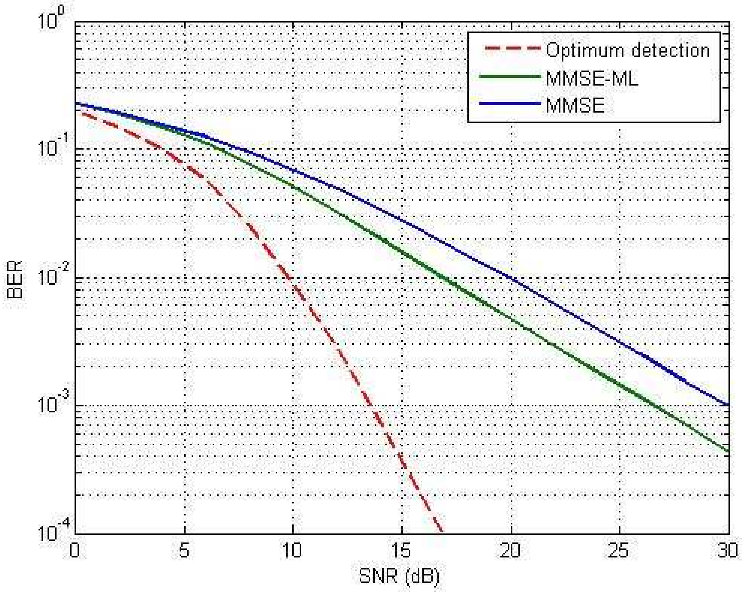

Fig.8. Performance of the MMSE-ML scheme for binary data in MIMO 4x4

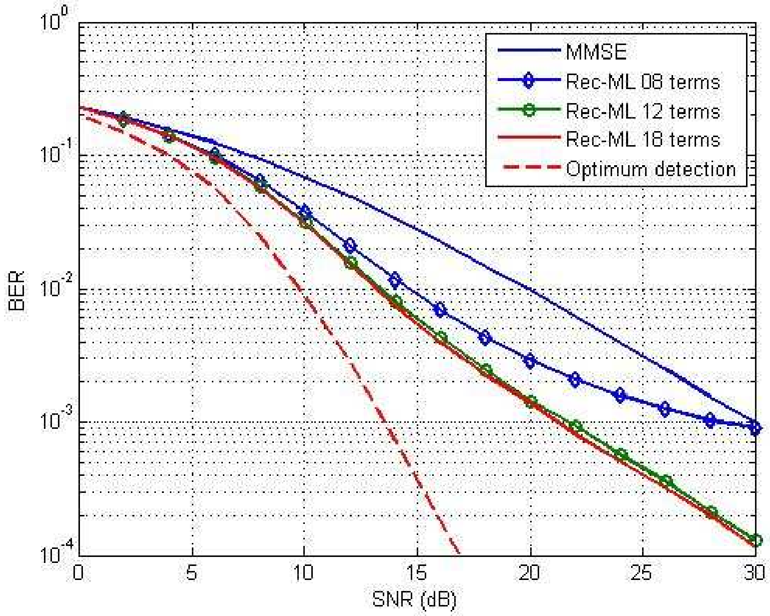

Fig.9. Performance of the Recursive-ML scheme for binary data in MIMO 4x4

6. Summary and conclusion

In the MIMO context, FBMC systems based on OQAM modulation have the potential to outperform OFDM systems based on QAM modulation, when ML techniques are employed. However, the interference term which comes with every real symbol in OQAM modulation is an obstacle in the ML processing and two approaches have been proposed to resolve the issue.

In the MMSE-ML scheme, the interference term is estimated through the MMSE technique, then the estimated value is subtracted from the received signals and the ML procedure is applied. The analysis of the scheme shows that the performance achieved is dependent on the elements of the transmission channel matrix and optimal detection can be reached for particular conditions. In the presence of random channels, averaging takes place and the results of simulation carried out for a Rayleigh flat fading channel, the MIMO 2x2 case and binary data, show a gain in BER corresponding to about 2 dB in SNR.
A remarkable feature of the MMSE-ML scheme is its simplicity, due to the fact that the data symbols are real. Multibit data in high order MIMO configurations can be processed with a reasonable level of computational complexity. Extension of the scheme to MIMO 4x4 is straightforward and simulation results have shown a gain of about 3 dB for binary data.

In an effort to come closer to optimal detection, the recursive-ML scheme has been proposed. It consists of computing every interference term from its definition, using estimated and detected data symbols. The complexity is increased and a delay is introduced in the approach. In order to minimize this additional delay and the complexity, partial reconstitutions of the interference tems have been considered. The gain in performance is significant but optimal detection is not reached. In fact, combination with error detection is required if optimal detection is targetted.

When FBMC systems and OFDM systems are considered for MIMO and spatial multiplexing, the two multicarrier schemes yield the same performance with the MMSE technique. However, with the ML technique, the situation is different and it appears that OFDM outperforms the schemes which have been presented for FBMC, as illustrated in Fig.10. This figure gives, for MIMO 2x2, the BER curves corresponding to MMSE, MMSE-ML, recursive-ML for FBMC and the BER curve for OFDM.

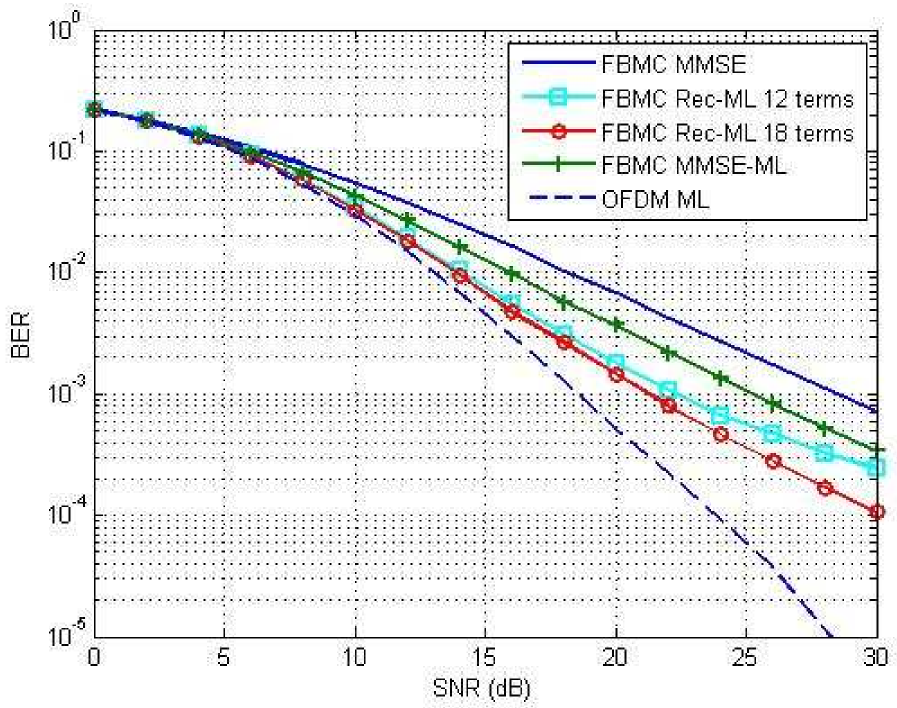

Fig.10. Comparison of FBMC schemes and OFDM, for MIMO 2x2

Now, in practice, considering the imprecision of the channel measurements, optimal performance cannot be reached and the performance gap between OFDM and the simpler FBMC/MMSE-ML approach might be small.

The software programs implementing the following algorithms have been delivered to WP9, for complexity assessment, system simulation, comparison with OFDM and possible inclusion in the hardware demonstrator

- MMSE-ML for MIMO 2x2 and binary data (OQAM-4)
- MMSE-ML for MIMO 2x2 and 2-bit and 4-bit data (OQAM-16 and OQAM-64)
- Recursive-ML for MIMO 2x2 and binary data (OQAM-4)
- MMSE-ML for MIMO 4x4 and binary data (OQAM-4)

The complexity of the FPGA implementation of the algorithm ‘MMSE-ML for MIMO 4x4 and binary data’ will be assessed by WP9.

References

[1] R.V. Nee, A.V. Zelst, and G. Awater, "Maximum Likelihood Decoding in a Space Division Multiplexing System", Proceedings of IEEE-Vehicular Technology Conference, VTC 2000-Spring, Tokyo, May 2000.

[2] X.Zhu and R.D.Murch, “Performance analysis of maximum likelihood detection in a MIMO antenna system”, IEEE Transactions on Communications, Vol.50, n°2, Feb.2002, pp. 187-191.

[3] N.Kim,Y.Lee and H.Park, “Performance analysis of MIMO systems withlinear MMSE receiver”, IEEE Trans. on Wireless Communications, vol.7, n°11, Nov.2008.

[4] M.El Tabach, J.P.Javaudin and M.Hélard, “Spatial data multiplexing over OFDM/OQAM modulations”, Proceedings of IEEE-ICC 2007, Glasgow, 24-28 June 2007, pp.4201-4206.

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