ITERATIVE MULTIUSER DETECTION PERFORMANCE EVALUATION ON A SATELLITE MULTIBEAM COVERAGE

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ABSTRACT

This paper deals with the use of non-linear multiuser detection techniques to mitigate co-channel interference on the reverse link of multibeam satellite systems. The considered system is inspired by the DVB-RCS standard, with the use of convolutional coding. The algorithms consist of iterative parallel interference cancellation schemes with semi-blind channel estimation. We propose a simple approach for statistical evaluation on a multibeam coverage, and present results obtained on a coverage designed on a digital Ka-band focal array feed reflector antenna.

1. INTRODUCTION

In areas with reduced infrastructure and low population density, satellite communication systems are good candidates to provide high data rate at low costs. Multibeam technology is a key component of these systems. A fundamental limitation is then Co-Channel Interference (CCI), when assimilated to additional noise at the demodulator level. However, this limitation can be at least partially overcome by the use of multiuser detection techniques.

We consider in this paper the use of these techniques to mitigate CCI on the reverse link of multibeam satellite systems which take as a starting point the DVB-RCS standard [1]. We first present the context, the model for digital beamforming, and the definitions used in our digital communication context. For simplicity, we limit ourselves to the use of convolutional codes on a symbol synchronous time-invariant channel. Extension to a symbol asynchronous channel is addressed in [2]. We then describe the considered algorithms, which basically consist of Parallel Interference Cancellation (PIC) schemes with semi-blind channel estimation. We finally propose simulation results to compare algorithm performances. A first set of results is presented on a fictitious interference configuration. However, on a reverse link, interference configuration depends on the user locations in each cell. In order to evaluate algorithm performances while taking into account this variability and allowing reasonable times of simulation, we propose a simple approximation consisting in an equivalent Signal to Noise plus Interference Ratio (SINR) measurement at the algorithm outputs. This approximation is used to provide results on a multibeam cov-
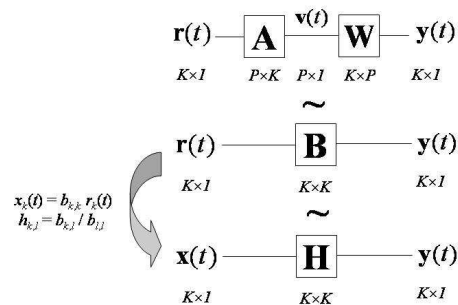

Figure 1 – Derivation of the receiver chain

erage designed on a digital Ka-band Focal Array Feed Reflector (FAFR) antenna.

2. SYSTEM ASSUMPTIONS AND MODEL

2.1 System outlines

We consider the reverse link of a fixed satellite service in Ka-band with a multibeam coverage. Following the DVB-RCS standard, we consider a MF(multi-frequency)-TDMA access. The satellite is assumed regenerative, with on-board multiuser detection. The reuse pattern is regular [3]. In such a context, the use of multiuser detection techniques for CCI naturally leads to modify the reuse strategy in order to increase the system capacity. This can be obtained by reducing the reuse number [4] or by reducing the cells radius compared to classical systems, for which it is not possible while keeping high carrier to interference ratios (C/I).

2.2 Model

In the following, we consider a given elementary channel, i.e. a frequency/time slot in the MF-TDMA frame. Notations are relative to complex envelops. $\cdot^{T}$, $\cdot^{H}$ and $\cdot^{*}$ denote respectively the transpose, conjugate-transpose, and conjugate operators. Consider K uplink signals coming from K locations in K different co-channel cells. Under the narrowband assumption [5], we get classically

$$\mathbf{v}(t) = \mathbf{A}\mathbf{r}(t) + \mathbf{n}^{(v)}(t) \qquad (1)$$

where $\mathbf{v}(t)$ is the $P \times 1$ vector of signals at the output of the P sources, $\mathbf{r}(t)$ is the $K \times 1$ vector of received signals, $\mathbf{n}^{(v)}(t)$ is the $P \times 1$ vector of additive noises on the P sources, and $\mathbf{A}$ is the $P \times K$ steering vectors matrix. This matrix depends

on the geometry of the array and on the user locations. Additive noises are assumed Additive White Gaussian Noises (AWGN) with a covariance matrix $E(\mathbf{n}^{(v)}(t)\mathbf{n}^{(v)}(t)^H) = \sigma^2 \mathbf{I}_P$, where $\mathbf{I}_P$ design the $P \times P$ identity matrix.

We consider a beamformer with fixed coefficients (i.e. the beamformer coefficients are identical for all users in a cell). We note $\mathbf{W} = [\mathbf{w}_1^T \ldots \mathbf{w}_K^T]^T$ the $K \times P$ matrix of beamformer coefficients for the K cells. Without loss of generality, we assume that $\mathbf{w}_k\mathbf{w}_k^H = 1$ for all k. The $K \times 1$ vector of signals at the beamformer output $\mathbf{y}(t) = [y_1(t) \ldots y_K(t)]^T$ is then given by

$$\mathbf{y}(t) = \mathbf{W}\mathbf{v}(t) = \mathbf{B}\mathbf{r}(t) + \mathbf{n}(t) \qquad (2)$$

where $\mathbf{B} = \mathbf{W}\mathbf{A}$ is the $K \times K$ beamforming matrix and $\mathbf{n}(t) = [n_1(t) \ldots n_K(t)]^T = \mathbf{W}\mathbf{n}^{(v)}(t)$ is the $K \times 1$ vector of additive noises at the beamformer output, with $\mathbf{R_n} = E(\mathbf{n}(t)\mathbf{n}(t)^H) = \sigma^2\mathbf{W}\mathbf{W}^H$.

We introduce the $K \times K$ normalized beamforming matrix $\mathbf{H} = [\mathbf{h}_1 \ldots \mathbf{h}_K] = (h_{k,l})$ with $h_{k,l} = b_{k,l} / b_{l,l}$, $x_k(t) = b_{k,k} r_k(t)$ and the $K \times 1$ vector $\mathbf{x}(t) = [x_1(t) \ldots x_K(t)]^T$. We finally get

$$\mathbf{y}(t) = \mathbf{H}\mathbf{x}(t) + \mathbf{n}(t) \qquad (3)$$

Notice that we have $h_{k,k} = 1$ for all k. The introduction of $\mathbf{H}$ and $\mathbf{x}(t)$ appears useful to define a signal to noise ratio (SNR) in the framework of digital communications. Its derivation is summarized in Fig. 1.

Regarding the waveform, the uniformly distributed information bits are convolutionally encoded, the coded bits are then mapped onto a QPSK constellation, and the symbols are finally interleaved differently on each beam (Fig. 2). A burst of N symbols $d_k[n]$ is composed of these interleaved symbols in which is inserted a training sequence. We model the signals $x_k(t)$ as

$$x_k(t) = \rho_k e^{j\varphi_k} \sum_{n=0}^{N-1} d_k[n] s(t - nT) \qquad (4)$$

where T, $s(t)$, ρ_k, φ_k, denote respectively the symbol duration, the normalized emitter filter response, the amplitude of the kth signal and its carrier phase, uniformly distributed on $[0, 2\pi]$. The channel model is summarized in Fig. 2.

2.3 Definitions

We define the signal to noise ratio for the kth signal on the kth beam as:

$$E_s/N_0|_k = \rho_k^2/\sigma^2 \qquad (5)$$

and the carrier to interference ratio for the kth signal on the kth beam as:

$$C/I|_k = \rho_k^2 \Big/ \sum_{l \neq k} |h_{k,l}|^2 \rho_l^2 \qquad (6)$$

Due to the spatial diversity of our model, we can obtain for each user a better signal to noise ratio than (5) by linearly combining the signals received on the different beams (assuming no interference, by coherently combining the signal of interest while noises are combined incoherently). We define the ratio between the SNR available by using all the beams and the SNR in (5) as a combining gain. The combining gain for the kth user can be derived by a spatial matched-filter [5] after noise whitening at the beamformer output, and is given by
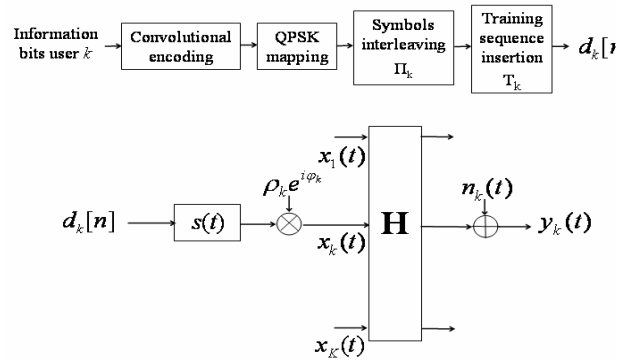

Figure 2 – Transmitter and channel model

$$\xi_k = \frac{(\mathbf{R_n}^{-1}\mathbf{h}_k)^H \mathbf{h}_k \mathbf{h}_k^H (\mathbf{R_n}^{-1}\mathbf{h}_k)}{(\mathbf{R_n}^{-1}\mathbf{h}_k)^H \mathbf{R_n} (\mathbf{R_n}^{-1}\mathbf{h}_k)} \qquad (7)$$

3.   DESCRIPTION OF ALGORITHMS

3.1   Assumptions for the design of algorithms

The design of algorithms is based on the following assumptions:

i) The matrices $\mathbf{B}$, $\mathbf{H}$ and $\mathbf{R_n}$ can be assumed time-invariant on a burst duration. However, it is difficult to assume a priori accurate knowledge of their coefficients at the receiver without calibration procedures or estimation at the receiver level, even with known user locations, because of satellite attitude variations and long-term drift of receiver chain. We consider here a semi-blind estimation scheme at the receiver level, assuming that an initial single user synchronization/demodulation step, by assimilating interference to additional noise, is made possible by beamforming.

ii) The combining gain (7) may appear limited. This raises the question of the usefulness to combine the received signals in order to recover it, more especially as algorithms with combining imply a higher complexity. In the following, we have chosen to consider both cases, with and without combining.

iii) We consider that significant interferers are only located in adjacent co-channel cells. Due to the regular reuse pattern, there are at most 6 significant interferers for each user [3].

3.2   Description of algorithms

After matched-filtering and optimal sampling, we can consider the classical "one-shot" approach with the model:

$$\mathbf{y}[n] = \mathbf{G}\mathbf{d}[n] + \mathbf{n}[n] \qquad (8)$$

where $\mathbf{G} = [\mathbf{g}_1^T \ldots \mathbf{g}_K^T]^T = (g_{k,l}) = \mathbf{H}\,\mathrm{diag}(\rho_k\exp(j\varphi_k))$,

$\quad \mathbf{d}[n] = [d_1[n] \ldots d_K[n]]^T$
$\quad \mathbf{y}[n] = [y_1[n] \ldots y_K[n]]^T$ with $y_k[n] = y_k(t) * s(-t) |_{t=nT}$
$\quad \mathbf{n}[n] = [n_1[n] \ldots n_K[n]]^T$ with $n_k[n] = n_k(t) * s(-t) |_{t=nT}$.

A synoptic of the receivers for the kth beam is given in Fig. 3, where interleaving and desinterleaving operations are omitted for simplicity. All operations are performed in parallel on the different beams, with exchange of information from one to another (noted with dashed lines in Fig. 3). In all the following, for any parameter c, $\hat{c}^{(m)}$ denotes an estimate or a decision on c at the mth iteration.
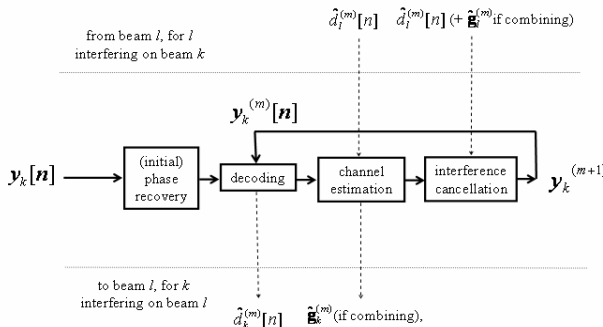
Figure 3 – Synoptic of receivers on the kth beam

3.2.1 Channel estimation

The channel estimation on the kth beam is processed by a least-square estimator using currently estimated symbols (and including pilot symbols). At the mth iteration, we get for the kth beam

$$\hat{\mathbf{g}}_k^{(m)} = \left(\sum_{n=1}^{N} y_k[n] \hat{\mathbf{d}}^{(m)}[n]^H \right) \left(\sum_{n=1}^{N} \hat{\mathbf{d}}^{(m)}[n] \hat{\mathbf{d}}^{(m)}[n]^H \right)^{-1} \quad (9)$$

We only use estimated symbols of the kth signal and of adjacent interfering ones (paragraph 3.1, assumption iii), which is not specified in the equation for notation simplicity.

3.2.2 Interference cancellation

Two different schemes of interference cancellation are considered, the first one without combining, and the second one with a Minimum Mean Square Error (MMSE) combining after interference cancellation.

For the first scheme, which is limited in term of achievable signal to noise ratio to the $E_s/N_0|_k$ of equation (5), we get for the nth symbol of the kth user at the $(m+1)^{th}$ iteration

$$y_k^{(m+1)}[n] = \hat{g}_{k,k}^{(m)*} \left(y_k[n] - \sum_{l \neq k} \hat{g}_{k,l}^{(m)} \hat{d}_l^{(m)}[n] \right) \quad (10)$$

For the second scheme, which can potentially recover the combining gain and achieve a signal to noise ratio $E_s/N_0|_k + \xi_k$ [dB] with ξ_k given by equation (7), we get for the nth symbol of the kth user at the $(m+1)^{th}$ iteration

$$y_k^{(m+1)}[n] = \hat{\boldsymbol{\eta}}_k^{(m)H} \tilde{\mathbf{y}}_k^{(m)}[n] \quad (11)$$

with

$$\tilde{\mathbf{y}}_k^{(m)}[n] = \mathbf{y}[n] - \tilde{\mathbf{G}}_k^{(m)} \hat{\mathbf{d}}^{(m)}[n]. \quad (12)$$

where

- $\tilde{\mathbf{G}}_k^{(m)}$ is $\hat{\mathbf{G}}^{(m)}$ with its kth column set to zero,

- $\hat{\boldsymbol{\eta}}_k^{(m)}$ is the estimated MMSE combiner.

This MMSE combiner is derived by modeling the residual interference plus noise as a random stationary process independent of the signal of interest, and is given by

$$\hat{\boldsymbol{\eta}}_k^{(m)} = \left(\sum_{n=1}^{N} \tilde{\mathbf{y}}_k^{(m)}[n] \tilde{\mathbf{y}}_k^{(m)}[n]^H \right)^{-1} \left(\sum_{n=1}^{N} \tilde{\mathbf{y}}_k^{(m)}[n] \hat{d}_k^{(m)}[n]^* \right) (13)$$

As for channel estimation, we limit the MMSE combiner estimation, and consequently combining, to the beam of interest and adjacent co-channel beams. Notice that $\mathbf{R_n}$ is indirectly estimated in (13).

3.2.3 Decoding algorithms

Two different algorithms are considered for decoding. For both, the residual interference plus noise (after desinterleaving) at the decoder input is assimilated to AWGN.

The first one consists of a Viterbi decoding, and provides symbol hard decisions, used in (9-10) in the case without combining and (9-12-13) in the case with combining.

The second one, referred to as Maximum A Posteriori (MAP) decoding, provides for coded bits a posteriori and extrinsic probability mass functions (pmf) through the use of the BCJR algorithm [6][7]. For MAP decoding without combining, the proposed scheme can be linked with theoretical approach of multiuser joint decoding [8] with estimation by Expectation-Maximization (EM) applied "locally" [9]. We use extrinsic pmf based symbol expectations for interference cancellation in (10), as a posteriori pmf based symbol expectations for interference cancellation is known to reduce the useful signal component [8]. The EM algorithm leads to use a posteriori pmf based symbol expectations for channel estimation in (9). For MAP decoding with combining, we use a posteriori pmf based symbol expectations in (9-12-13). The equivalent signal to noise ratio at the input of the MAP algorithm is estimated by the M2M4 estimator [10].

3.2.4 Initialization

The initial phases are estimated by the Maximum Likelihood Data-Aided (ML-DA) single user estimator on the training sequences. Notice that no direct channel estimation (i.e. of $\mathbf{g}_k$) is performed for initialization.

4.   SIMULATION RESULTS

4.1   Comparison of algorithms

We consider the following simulation parameters (inspired by the DVB-RCS standard):
- rate 1/2 non recursive non systematic convolutional code with constraint length 7, and generators (133,171),
- packets of 53 information bytes (ATM cell), or 430 information symbols with closed trellis,
- training sequences of 32 symbols.

New random interleavers and training sequences are generated at each packet. No optimization is done for training sequences or interleavers as this would not be possible for a symbol asynchronous channel. We consider a target Bit Error Rate (BER) of $2 \cdot 10^{-4}$. This BER leads to a quasi error free scheme when assuming the classical scheme with outer Reed-Solomon and inner convolutional codes with infinite interleaving. It is assumed indicative for a burst access. It is reached on AWGN channel for $E_b/N_0 = 3.2$ dB.

In all the following, we consider that all users have the same E_b/N_0. In this case, carrier to interference ratio (6) simplifies to

$$C/I|_k = 1 / \sum_{l \neq k} |h_{k,l}|^2 \quad (14)$$

We consider in a first time a fictitious configuration, i.e. given matrices $\mathbf{H}$ and $\mathbf{R_n}$, with 14 users. The ranges of C/I and of combining gains (depending on the user) are respectively from 2 to 6 dB and from 0.8 to 2.1 dB. An example of
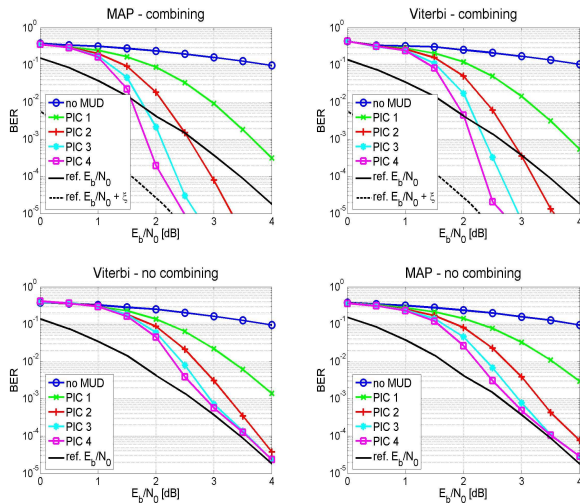
Figure 4 – BER results for the different algorithms

BER for a user k with $C/I|_k = 3$ dB and a combining gain $\xi_k = 1.9$ dB is proposed in Fig. 4.

Algorithms without combining exhibit degradations with respect to E_b/N_0 single user reference of about 0.1/0.2 dB after 3 iterations.

Algorithms with combining allow better results. However, their degradation with respect to $E_b/N_0 + \xi_k$ single user reference is relatively important: 0.7/0.9 dB in 4 iterations. In fact, some other users l with lower combining gains reach their single user $E_b/N_0 + \xi_l$ reference (results not reported). On the contrary, users with high combining gains, as the considered one k, show a more important degradation as they are limited by imperfect interference cancellation of interferers l with smaller combining gains.

Considering decoding algorithms, MAP decoding logically allows slightly better results than Viterbi decoding, with and without combining.

In the following, we limit the study to the algorithms which give the best results: MAP with combining, and the worst results: Viterbi without combining.

4.2   Approximation by SINR measurements

An essential difficulty for the study of a multibeam coverage is the variability of interference configurations with the user locations. In order to evaluate algorithm performances on a given multibeam coverage, we should run a Monte-Carlo simulation for each configuration, and this for a high number of configurations. In order to reduce the computation effort for such an evaluation, we propose a very simple approach. It consists in computing an equivalent SINR for each user at the algorithm output, by assuming residual interference plus noise AWGN. An approximated BER can then be derived from these SINR by tabulating the BER results of the code on AWGN channel. The advantage is that average SINR for a given configuration can be obtained by computing a short simulation, since they require a much smaller statistical sample to converge than average BER. We use for SINR measurements the signal to noise ratio estimator ML-DA [10] (which takes into account imperfect synchronization effects).
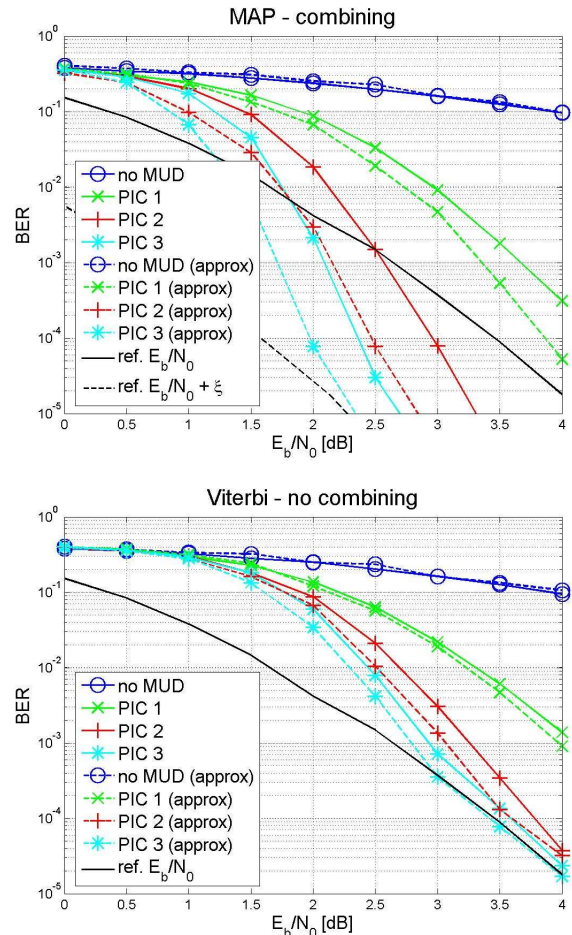

Figure 5 – BER results: simulation and approximation

Figure 5 proposes a comparison of measured BER and approximated BER derived from SINR measurements. The considered user and configuration are the same than in paragraph 4.1. For both considered algorithms, approximation by SINR measurements gives optimistic results. It appears quite accurate for the case of Viterbi without combining (offset ~ 0.2 dB), less for the case of MAP with combining (offset ~ 0.5 dB). Complementary simulations for other algorithms and configurations have shown that the approximation appears quite accurate for algorithms without combining, whereas for algorithms with combining it leads to optimistic results, increasingly as C/I decrease and combining gains increase.

4.3   Evaluation on a multibeam coverage

We propose in this paragraph some results obtained with the previous approximation on a coverage designed on a digital Ka-band FAFR built from an existing design of Multikara front-end [11]. We limit ourselves to an area of 1600×2700 km. The multibeam coverage then consists of 54 cells of radius 0.25° with a reuse number of 3. We study the frequency band A (Fig. 6), with 18 cells. Beamforming coefficients **W** are optimized in term of worst case antenna gain and worst case antenna C/I by mean of a dedicated antenna software.

The user locations are assumed independent from a cell to another and uniformly distributed on each cell. We still
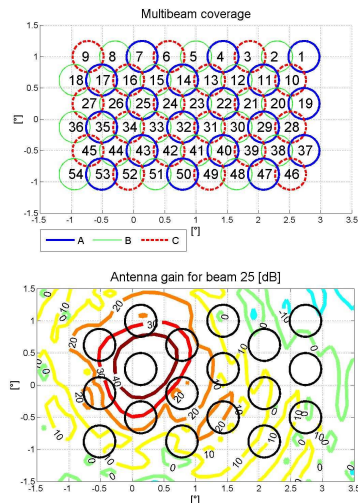
Figure 6 – The multibeam coverage

Figure 7 – Results in term of percentage of failure

consider that all users have the same E_b/N_0. We obtain a range of C/I values from -1 to 23 dB, and a range of combining gains from 0 to 2 dB. The C/I mean value is 10.5 dB, and the combining gain mean value is 0.5 dB. For simulation purpose, we use the model of paragraph 2.2 with simulation parameters of paragraph 4.1. SINR are computed as in paragraph 4.2. Results in term of percentage of failure (i.e. of users for which the target SINR of 3.2 dB is not reached) for frequency band A are shown in Fig. 7. We consider a target percentage of failure of 0.01 %.

This target percentage can not be reached without multiuser detection, even at very high E_b/N_0. Whatever the algorithm, 2 iterations are necessary to reach it with a limited degradation (and the gain beyond 2 iterations is negligible). MAP with combining leads to the best results. However, the gain with respect to Viterbi without combining appears relatively small: 0.2 dB. The higher complexity of the MAP with combining algorithm is consequently hardly justified by this gain.

Clearly, this result is partly due to the dimensioning of the coverage. A reuse number of 1 would lead to higher combining gains and potentially better results for algorithms with combining. However, it can not be implemented because too small C/I would prevent initial single user synchronization/demodulation (paragraph 3.1. assumption i). For a reuse number of 3 or more, system capacity considerations lead naturally to consider reduced cell radius. This leads to relatively small combining gains for most of locations in a cell.

It must also be noticed that the relative performance of algorithms can be dependant of the user power configuration (we have assumed here that all users have an equal E_b/N_0, i.e. an equal power after beamforming). However, other simulations with equal user power before beamforming have lead to comparable results.

5. CONCLUSION

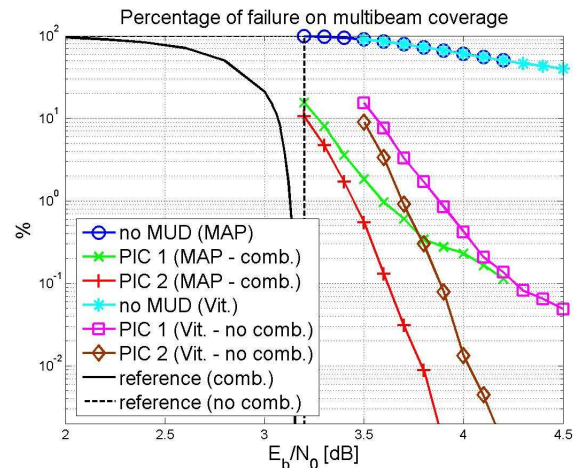In this paper we have compared several iterative multiuser detection algorithms with semi-blind channel estimation in a multibeam satellite context. An approximation through an equivalent SINR measurement has been introduced. This approximation has allowed us to obtain results on a multibeam coverage, taking into account the variability of interference configuration with the user locations. It has appeared that algorithms with combining lead to only a reduced gain with respect to those without combining on the considered multibeam coverage.

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