Performance of a Nonlinear Adaptive SBS-MAP Detector Using Soft-Statistics for Digital Transmissions over HF Channels

E. Baccarelli, R. Cusani, and S. Galli

***Abstract*—The effectiveness of the recently proposed adaptive Maximum A Posteriori (MAP) receiver in Cusani and Mattila is verified for digital HF links between mobile and/or fixed units. Following Cusani and Mattila, a suitable MAP algorithm is employed to compute Symbol-by-Symbol (SBS) the A Posteriori Probabilities (APP's) of the channel state; from these, the detected data stream is obtained. The same APP's are employed by an adaptive nonlinear Kalman-like filter to estimate recursively the time-varying channel with fast convergence and good tracking properties, overcoming the delay problem suffered by conventional adaptive MLSE-VA detectors. Computer simulations allow to compare the adaptive SBS-MAP with other receivers (DFE, MLSE) and verify its effectiveness in the HF environment.**

***Index Terms*—Channal estimation, HF link, MAP equalizer.**

I. INTRODUCTION: THE HF CHANNEL AND THE TWO-RAY MODEL

DIGITAL radio links over the HF band (3–30 MHz) are widely employed in many civilian and military applications and, in particular, for data communications with air and sea mobile units. In fact, HF links are typical not only for military communication systems, but also for civilian ships and aircrafts crossing over transoceanic routes [1, Ch. 1].

The physical features of the HF channel have been largely investigated in the past years (see, for example, [1, Sect. 1.2.4] and references therein): it is typically affected by diffraction, scattering and multipath phenomena, which introduce temporal spread and frequency selectivity in the received signal, while the temporal variations of the heights of the atmosphere layers make the channel time-varying and induces Doppler-spread and Doppler-shift effects. Typical values are 1–2 ms for the time spread τ_S and 1–2 Hz for the Doppler spread B_D [1, Ch. 1]. Additional Doppler effects are induced by the speed of the mobile units.

The time-varying and frequency-selective fading induced by the multipath generates a severe inter-symbol interference over the received digital signal, which is also affected by additive noise (thermal noise plus interferences). Although up to five different Rayleigh-fading rays can be reflected from the ionosphere layers [1, Ch. 1], accurate modeling of the HF link is generally obtained by taking into account two-rays only, spaced τ s apart. In this case, the equivalent baseband (complex) received signal can be modeled as

$$z(t) = g_1(t)s(t) + g_2(t)s(t-\tau) + n(t) \tag{1}$$

where $s(t)$ is the digitally-modulated transmitted signal; $n(t)$ is a complex white noise (typically, Gaussian) stationary process, with independent components and two-sided power spectrum level $N_o/2$ (V^2/Hz); the fading processes $g_1(t), g_2(t)$ are two independent zero-mean complex Gaussian stationary processes with independent components, taking into account for Rayleigh-distributed multipath phenomena. These fading processes are also assumed to share the same Gaussian power spectrum shape (Watterson model [1], [2]) and then the same Doppler spread B_D (Hz),[1] but they generally may exhibit different powers. A residual frequency shift Δf (Hz) can be eventually present on the baseband received signal, due to residual (uncompensated) carrier tracking offset in the demodulation process, and can be modeled by multiplying $z(t)$ with the complex exponential $\exp(j2\pi\Delta ft)$.

The equivalent discrete-time (sampled at symbol interval T_S) Channel Impulse Response (CIR) at time nT_s is constituted by L_c main taps $c_1(n), \ldots, c_{Lc}(n)$, obtained from $g_1(t), g_2(t)$ on the basis of the lowpass interpolation operated by the receiver filter. Ideal square-root raised-cosine transmitter and receiver filters with roll-off factor equal to 0.2 have been assumed in this paper. Although $g_1(t), g_2(t)$ have been assumed mutually independent, due to the (equivalent low-pass) filtering operated at the receiver font-end the (complex Gaussian) tap-processes $c_1(n), \ldots, c_{Lc}(n)$ are generally correlated, and the common assumption of uncorrelated scattering may fall short. The resulting CIR (complex) vector process $\underline{c}(n) \equiv [c_1(n), \ldots, c_{Lc}(n)]^T$ is then completely characterized by the sequence of (generally, nondiagonal) autocorrelation matrices $R_c(m) \equiv E\{\underline{c}(n)\underline{c}^H(n+m)\}$, with $m \geq 0$ ($\underline{v}^T$ denotes the transpose of the vector $\underline{v}$ and $\underline{v}^H$ the transpose conjugate).

From the above modeling, the equivalent discrete-time (T_S-sampled) baseband (complex) channel models the received sequence $r(n)$ as

$$r(n) = \sum_{i=0}^{L_C-1} c_i(n)b(n-i) + w(n) \tag{2}$$

where $b(n)$ is the transmitted data sequence (e.g., $b(n) = \pm 1$ for BPSK and $b(n) = (\pm 1 \pm j)/\sqrt{2}$ for QPSK) and $w(n)$ are the noise samples at the output of the receiver filter.

[1]For a Gaussian Doppler spectrum, the Doppler spread B_D is defined as the 3-dB bandwidth.

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Despite of its simplicity, the two-wave Rayleigh channel is not easy to equalise. First of all, the time spread τ_S (and then the CIR length L_c) may span over many symbol periods, in particular for values of τ nearly equal to $T_S/2$ (plus, eventually, multiples of T_S) as it is evidenced by the illustrative examples of Fig. 1 for some values of τ and T_S. Secondly, the two-ray channel exhibits a limited form of "temporal diversity" and catastrophic channel configurations can sometimes occur, e.g., when the two rays fade simultaneously [1, Ch. 1]. Thirdly, the Doppler spread B_D can be so large (compared to the symbol rate T_S^{-1}) that the channel varies significantly from symbol to symbol; such fast-fading is verified when the product $B_D T_S$ is of the order of 10^{-3} or larger.

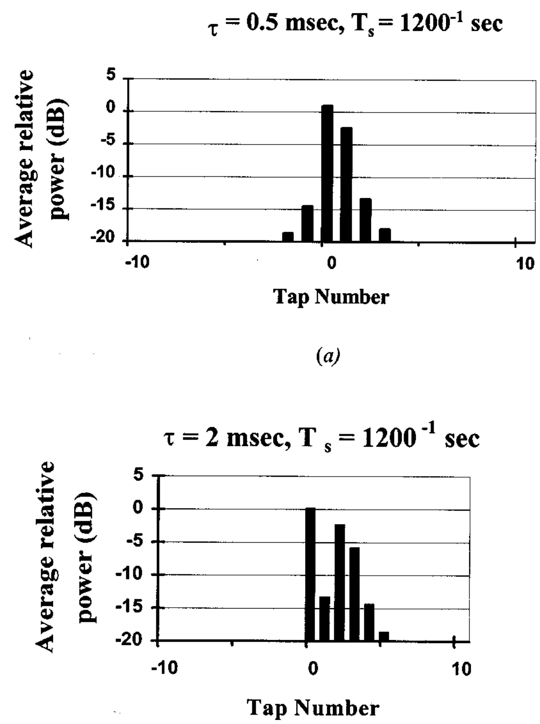
The above-described channel environment makes necessary to employ a powerful adaptive receiver to reliably recover the transmitted data. The basic requirements for data detection over fast-fading channels are pointed out in the following Section II, where some recent solutions are reviewed in short. The adaptive Maximum A Posteriori (MAP) receiver of [3] is shortly described in Section III. Its performance is analyzed in Section IV via computer simulations and compared with existing techniques, thus verifying its effectiveness. Finally, some conclusions are drawn in Section V.

II. Equalisation of Fast-Fading Channels: Previous Results and Basic Requirements

The classic adaptive Decision-Feedback Equaliser (DFE) and Maximum Likelihood Sequence Estimation (MLSE) receivers have been largely investigated in the past decade (see, for example, [4] and its references). The adaptive DFE equalisers [employing LMS or RLS algorithms for tap updating [5, Ch. 6] are characterized by inherent simplicity and robustness but are affected by error propagation and noise enhancement phenomena [6]. The adaptive MLSE generally outperforms the DFE but its complexity is much larger, although several reduced-complexity solutions have been proposed [1, Ch. 2–3]. Moreover, the adaptive MLSE implies the presence of a channel estimator (e.g., an LMS estimator or a Kalman-like filter) which exploits the MLSE output decisions to perform channel tracking. However, the MLSE delivers such decisions with a large delay (equal to four or five times the CIR length L_c [5]) so that the available channel estimate is delayed with respect to the true channel trajectory, with a consequent performance loss for the overall receiver [7]. Alternative MLSE structures (e.g., employing short-delay "tentative" decisions and large-delay "final" decisions) only mitigate the above problem [1, Ch. 3].

The recently proposed Per-Survivor Processing receivers [7], where a channel estimate is retained for each of the possible "surviving" paths of the trellis of the Viterbi Algorithm (VA), exhibit nearly-optimal performance (in a Maximum Likelihood Sequence sense) but their complexity seems to be quite large, in general.

The above-described decision-delay problem can be overcome by operating on the received data Symbol-by-Symbol (SBS) decisions instead of sequence estimates (as done by the MLSE). This is the approach followed for example in [8], where the Bayesan DFE, assisted by a channel estimator, generalizes and outperforms the DFE structure working with a short decision-delay (a few symbol intervals). Good performance is thus obtained for fast-fading channels.



(a)

(b)

Fig. 1. Illustrative power/delay profiles for an HF channel with two equal-power τ-spaced rays (sampling interval $T_s = 1200^{-1}$ s). The profiles in (a) and (b), respectively, correspond to the "good" and "poor" CCIR test channels [1], [2].

The Bayesan conditional DFE proposed in [9] for blind equalization of stationary (fixed) channels combines a SBS-MAP estimator (designed for the case of known channel) with a recursive channel estimator. This gives a *sub-optimal* solution with reduced complexity (which is linear in the estimation lag, instead of exponential). However, in [9] such as in other previous contributions following a similar approach (see [9]), the *fast-fading* channel case is not considered. Moreover, in [9], the CIR is estimated on the basis of hard-decided data, so that detection errors may lead to inaccurate channel estimates and eventually to tracking loss, when the channel varies rapidly.

III. The Adaptive Symbol-by-Symbol MAP Receiver

An alternative solution to the channel tracking problem can be obtained by feeding the channel estimator with "soft-statistics" (SS's) in place of the usual "hard-statistics" constituted by the detected data. This constitutes the basic feature of the receiver proposed in [3] for specific applications to the land-mobile radio channel, which also delivers the SS's with a very small delay (of the order of the CIR length L_c) and thus allows reliable tracking of fast channel variations.

The SBS-MAP algorithm employed in [3] belongs to the Abend-Fritchman family [10]. It starts from the definition of the *channel state* at step n as the L-variate vector $[b(n) \ldots b(n-L+1)]^T$ of the last L transmitted symbols, being L the channel length assumed by the receiver [possibly, equal to L_c of (1)]. The A Posteriori Probabilities (APP's) of

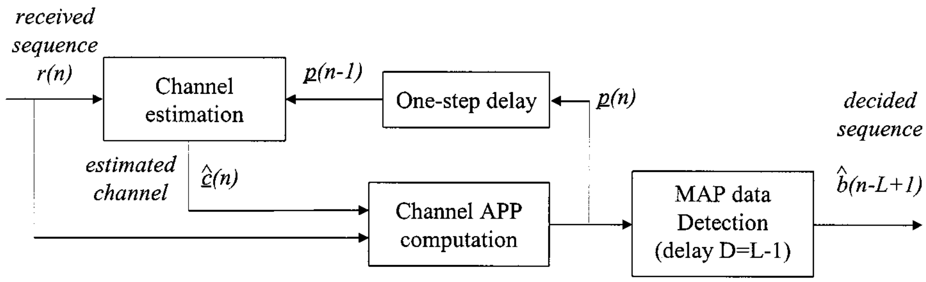


Fig. 2. Block diagram of the adaptive SBS-MAP detector.

the channel state at step n are then calculated from the known (or reliably estimated) CIR and on the basis of the noisy data samples $r(1), \ldots, r(n)$ received until step n. From the channel APP's at step n, collected in the APP's vector $\underline{p}(n)$, the APP's of each constellation symbol possibly transmitted at step $n-D$, with $D=L-1$, is then directly obtained by summing over the elements of $\underline{p}(n)$ corresponding to the channel state determinations having that symbol as $(L-1)$-th component [11, Sect. III]. Following the MAP decision rule (which, for equiprobable symbols, is equivalent to the Maximum Likelihood rule), the constellation symbol with maximum probability finally gives the detected symbol $\hat{b}(n-D)$ step-by-step, with a decision delay $D=L-1$ equal to the CIR memory length assumed by the receiver [11, Sect. III].

Many different SBS-MAP detectors have been proposed in the past years, with the purpose of complexity reduction with respect to the original algorithm of [10] which exhibit the same performance and, in principle, are substantially equivalent (see, for example, [11] besides the mentioned [9]). We observe here that also the MLSE makes soft statistics available (as in the well-known Soft-Output VA solutions exploited, for example, in turbo-decoding schemes) but again with large delay.

Referring now to the channel estimation problem, classic decision-driven solutions (e.g., Kalman filters) estimate the channel on the basis of the available hard-detected data ([1, Ch. 2]) while in [3] it is recursively computed on the basis of the SS's constituted by the APP's vector $\underline{p}(n)$, as shown in the block diagram of Fig. 2, via a recursive nonlinear adaptive Kalman-like filter. This is designed by modeling the evolution of $\underline{c}(n)$ as a zero-mean Gauss-Markov stationary first-order L-variate Auto-Regressive (AR) random process according to the usual relationship

$$\underline{c}(n) = A\underline{c}(n-1) + \underline{d}(n) \tag{3}$$

where the (complex vector) driving sequence $\underline{d}(n)$ is constituted by L independent zero-mean white Gaussian (complex) stationary processes with independent real components; A is an $L \times L$ (real) state transition matrix whose entries depend on the correlation coefficients actually exhibited by the CIR fading processes [9]. Such a simple model is commonly assumed to describe fading processes and develop recursive Kalman-like channel estimators [1, Ch. 6, 7]. The simulation results, reported in Section IV, confirm that it gives good receiver performance even when the true fading spectrum is Gaussian-shaped, as typical of HF channels.[2]

[2]The adaptive SBS-MAP detector can be generalized to the case of higher-order AR fading spectra by exploiting the property that an L-variate AR process of order n can be represented as a first-order nL-variate AR process.

During the transmission of training sequences ("data-aided" mode, for channel acquisition and tracking) the channel state is known and the APP's vector $\underline{p}(n)$ is constituted by all zeroes but a "one". The same channel estimator above described is then employed by using such APP's vector and forcing to zero the error covariance matrix employed in the calculation of the filter gain [3].

IV. Simulation Results and Performance Comparisons

The two-ray HF channel model (1) is characterized by the parameters τ, B_D, N_o and Δf, having assumed that the two paths have equal power. On the other hand, the SBS-MAP receiver assumes a certain channel length L and a known noise level N_o in the computation of the APP's and of the channel estimate. For channel estimation purposes, it also employs the matrices A and $R_c(0)$ describing the AR channel model of (3). From (3), the matrix A depends on $R_c(1)$ and then is tied to the Doppler spread B_D. As a practical choice, in the computer simulations the matrix A has been set by assuming that the CIR is constituted by L equal-power Rayleigh-distributed independent fading taps evolving as first-order AR processes with correlation coefficient a_o very close to unity. This gives: $R_c(0) = P_c I_{L\times L}$ and $A = a_o I_{L\times L}$, with $P_c = (2L)^{-1}$ for normalization purposes. In particular, in the computer simulations we have set: $a_o = 0.9999$, and N_o as corresponding to a signal-to-noise ratio (SNR) of 15 dB.

Performance tests have been carried out via Montecarlo trials by assuming QPSK modulation at 1200 baud (i.e., 2400 bps). A comparison with the adaptive LMS-DFE and with the adaptive MLSE-VA assisted by a Kalman filter for channel tracking purposes (K-VA solution) is also reported. The implemented adaptive DFE operates with detected symbols being fed back during the data-detection mode and with zero decision delay (in the sense of [12, Sect. I], i.e., the number of anti-causal feed-forward taps is zero); the sizes (n, k) of the feed-forward and feedback sections have been chosen for each kind of simulated channel by testing several values and selecting those resulting in the lower Bit Error Rate (BER). Similarly, the step-size parameter of the LMS algorithm for updating the taps of the DFE has been chosen as that giving the minimum BER for each simulation point. For reference purposes, the ideal adaptive DFE (with correct symbols being fed back) has also been simulated.

Following the suggestion of [5, Sect. 6.7], in the implemented K-VA solution the decision-delay D has been set equal to five times the assumed channel memory, i.e., $D = 5(L-1)$. The employed Kalman filter is the same described in Section III for

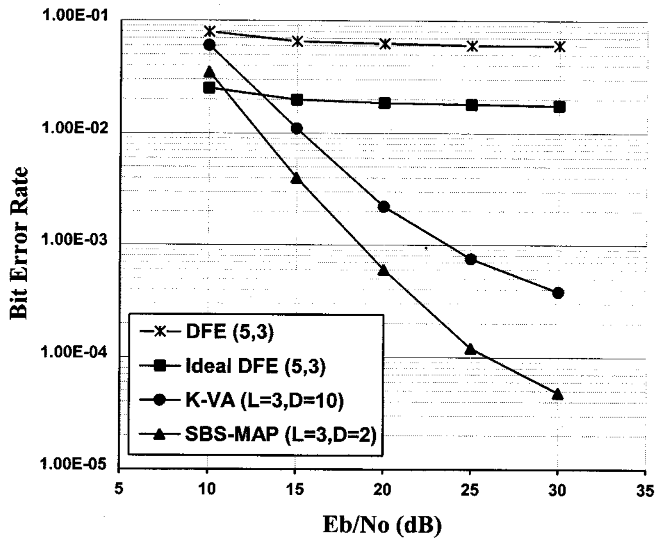


Fig. 3. Performance of the adaptive SBS-MAP detector for the three-tap reference channel (three paths Rayleigh-distributed and T_s-spaced; Gaussian Doppler spectrum with Doppler spread $B_D = 1.2$ Hz, QPSK modulation at 2400 bps, $L_{\rm fra} = 100$, throughput $\rho = 0.7$) and comparison with the adaptive LMS-DFE and K-VA solutions. D is the decision-delay employed by the K-VA and by the SBS-MAP. L is the channel length assumed in the implementation of both K-VA and SBS-MAP detectors.

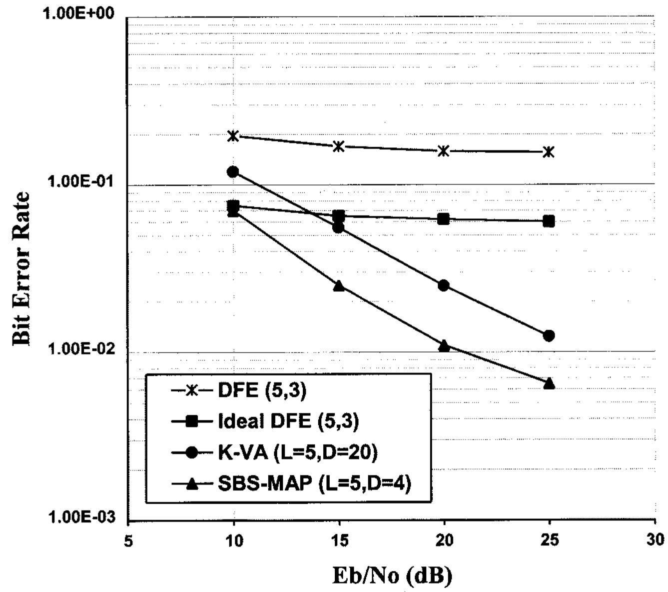


Fig. 4. Performance of the adaptive SBS-MAP detector for the "Poor" channel (two Rayleigh-distributed rays spaced apart $\tau = 2$ msec, Gaussian Doppler spectrum with Doppler spread $B_D = 1$ Hz, QPSK modulation at 2400 bps, $L_{\rm fra} = 100$, throughput $\rho = 0.7$) and comparison with the LMS-DFE and K-VA solutions. D is the decision-delay employed by the K-VA and by the SBS-MAP detectors.

the case of known data symbols but using the hard-decisions (with delay D) delivered by the VA in place of the known symbols ("decision-driven" operating mode).

The transmitted data stream is constituted by the alternance of training sequences, constituted by $L_{\rm pre}$ known symbols, and data blocks of $L_{\rm fra} - L_{\rm pre}$ symbols, so that the resulting net throughput is $\rho \equiv 1 - L_{\rm pre}/L_{\rm fra}$. No form of channel coding or differential modulation has been considered. In the detection of a data block neither the VA nor the SBS-MAP exploit the knowledge of the data symbols in the training sequence which follows the data block (although we expect that exploiting such knowledge the MLSE may obtain slightly larger benefits than the SBS-MAP).

Some simulation results are reported in Figs. 3–5 in terms of BER versus SNR curves. A reference channel with three Rayleigh-distributed, T_S-spaced paths and Gaussian-shaped fading Doppler spectrum is considered in Fig. 3 and in this case L has been set equal to L_c. The "poor" and "good" CCIR test channels [1], [2] with two τ-spaced paths and power/delay profiles reported in Fig. 1(a) and (b) have been assumed in Figs. 4 and 5, respectively. For the "poor" channel L has been chosen large enough so that the neglected taps of the equivalent T_S-sampled CIR's convey a negligible power. For the "good" channel the effective CIR length L_c is indeed larger than the assumed L [see Fig. 1(a)]: this explains the BER floor in Fig. 6, which is essentially due to residual (uncompensated) inter-symbol interference. The performance curves pertaining to the "moderate" CCIR channel [2], not reported here, exhibit a behavior similar to those of the "poor" channel.

From the performance plots, the effectiveness of the proposed solution can be verified: in the assumed conditions the SBS-MAP detector largely outperforms the LMS-DFE and the K-VA in all the considered cases and in particular the SNR gain over the K-VA ranges from 5 to 10 dB for the "three-taps" and "poor" channels. However, it must be considered that for a given ρ the BER depends on the frame length $L_{\rm fra}$ (equal to 100 in the simulations) because of the bias due to unreliable decisions at the end of the block. Large values of $L_{\rm fra}$ probably would reduce such bias in both receivers and then their performance difference would reduce. Alternative framing strategies consider the use of a postamble, as discussed for example in [13] for mobile digital radio channels.

In Figs. 3–5, the (uncompensated) frequency offset Δf has been assumed zero. Further simulation results (not reported here) show that the robustness of the SBS-MAP detector to nonzero frequency offset Δf is nearly the same of the K-VA and that all receivers (including the DFE) give unsatisfactory performance for Δf larger than 3–4 Hz.

V. Computational Issues and Conclusions

Regarding the computational aspects of the adaptive SBS-MAP receiver, it is known that the complexity of MAP algorithms is substantially of the same order of the MLS-VA detectors for the decision-delay $D = L - 1$ here considered (see, for example [11, Table I]). On the other hand, the structure of the channel estimator described in Sect. 3.2 is analogous to that of the classic Kalman tracker of ([5], Sect. 6.8), even though it is supplied by the APP sequence $\underline{p}(n)$ in place of the detected data. As a consequence, the complexity of the proposed receiver is nearly the same of the standard RLS-MLSE adaptive detectors [1, Ch. 6, 7], [5, Sect. 6.8].

The adaptive SBS-MAP detector of Fig. 2 using soft-statistics for channel estimation purposes is then verified to outperform previous solutions such as the adaptive MLSE-VA, with a comparable complexity, and then constitutes a good candidate

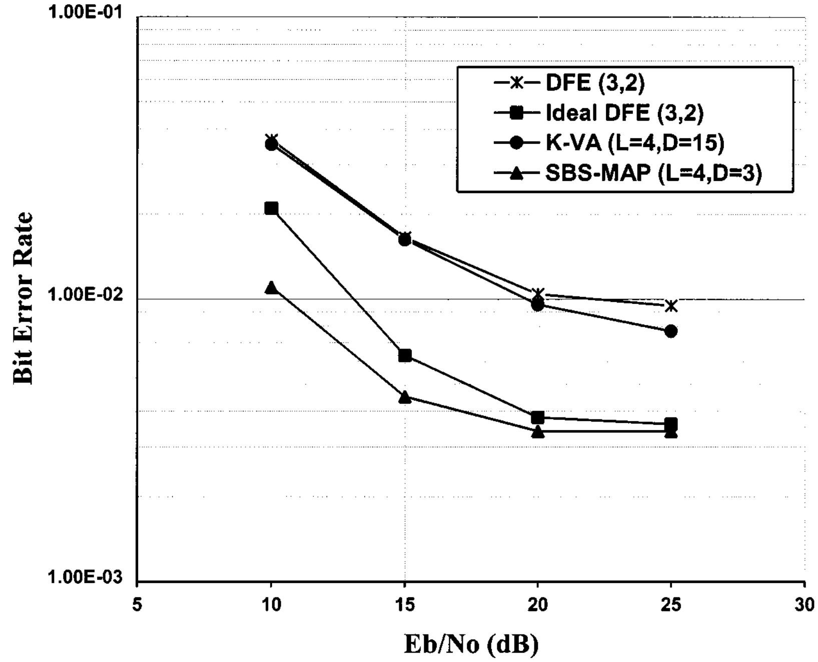


Fig. 5. The same as in Fig. 4, for the “Good” channel ($\tau = 0.5$ msec, $B_D = 0.1$ Hz).

for data transmission over the HF band between mobile and/or fixed units. Full comparison with a Per-Survivor Processing receiver properly designed for the HF channels requires a more accurate cost/performance analysis.

Finally we observe that when τ is large the HF channel is “sparse” (a few powerful CIR taps are spaced by many negligible taps) and the SBS-MAP equaliser can be simplified, as shown in [14].

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