INTERNATIONAL JOURNAL OF SATELLITE COMMUNICATIONS AND NETWORKING
Int. J. Satell. Commun. Network. 2015; **00**:1–16
Published online in Wiley InterScience (www.interscience.wiley.com). DOI: 10.1002/sat

Link Adaptation in Mobile Satellite Links: Schemes for Different Degrees of CSI Knowledge

Alberto Rico-Alvariño, Jesus Arnau and Carlos Mosquera

SUMMARY

We consider the problem of modulation and coding scheme selection in the return link of a mobile satellite system. We propose to use an affine combination of both open loop and closed loop signal quality indicators to perform this selection. The combination weights are dynamically adapted according to the ACK/NAK exchange between both ends, without making any assumptions on the channel distribution; this adaptation procedure is obtained as a stochastic programming solution to an optimization problem. We further extend our analysis to the particular case of not having information on the channel state, exploiting only ACK/NAK exchange for the rate selection problem. Simulation results will show the good performance of the proposed affine combination method compared to previous algorithms, and its robustness to environment changes. Copyright © 2015 John Wiley & Sons, Ltd.

Received ...

KEY WORDS: MCS selection, link adaptation, rate adaptation, mobile satellite, open loop, stochastic programming

1. INTRODUCTION

Link adaptation is the process of selecting an appropriate modulation and coding scheme (MCS) for each condition of a time-varying channel. This adaptation requires some sort of channel state information (CSI), such as signal to noise ratio (SNR), for example. The transmitter can get this information in two possible ways: open loop and closed loop, depending on which communication end measures the channel quality (see Figure 1).

Open loop CSI acquisition is based on channel reciprocity, i.e., on the fact that channels in the uplink and downlink can be strongly correlated, as is the case in time division duplexing (TDD) systems, for example. In such acquisition, the transmitter performs measurements directly on the incoming signal from the other end, and derives CSI from them. On the other hand, closed loop acquisition relies on the receiver estimating the channel response and feeding it back to the transmitter, usually through a limited feedback channel. Most frequency division duplexing (FDD) communication operate exclusively in closed loop mode due to the lack of channel reciprocity between different frequency bands. However, information from another frequency band can still be exploited if there exists sufficient correlation [2].

*Alberto Rico-Alvariño is with Corporate Research and Development, Qualcomm Technologies Inc. Address: 5775 Morehouse Drive, San Diego CA 92121, USA. email: albertor@qti.qualcomm.com
Jesus Arnau is with the Mathematical and Algorithmic Sciences Lab, France Research Center, Huawei Technologies Co., Ltd. Address: 20 Quai du Point du Jour, 92100 Boulogne-Billancourt, France. email: jesus.arnau@huawei.com
Carlos Mosquera is with the Signal Theory and Communications Department, Universidade de Vigo. Address: EE Telecomunicacion, Campus Universitario 36310 Vigo, Spain. email: mosquera@gts.uvigo.es
Parts of this paper were presented at the ASMS/SPSC 2014 conference [1].

After the CSI acquisition stage, the transmitter selects an MCS for transmission. A typical approach is to assign MCS to SNR values by means of a look-up table (LUT), which has to be built by performing exhaustive simulations to determine the performance of the different MCS, often assuming additive white Gaussian noise (AWGN) conditions. This procedure is common in satellite communications, where hysteresis [3–5] is sometimes included to prevent excessive ping-pong between consecutive MCS.

However, in practical scenarios the mapping between CSI and performance in AWGN may not be accurate: channels are time varying, receivers of different manufacturers may implement detection algorithms of different complexity, etc. To overcome this problem, backoff margins that depend on the statistical characterization of the channel have been introduced [3, 6].

These margins can be designed by following an LUT-based approach: again, exhaustive simulations are performed in many different scenarios, and the corresponding margins are calculated. These margins are stored in an LUT that is accessed by the transmitter to perform MCS selection. This implies that the simulations have to be representative of the scenarios where the communication system is going to operate, and that the transmitter is able to identify its environment. In consequence, this approach works only under controlled scenarios with calibrated receivers, and when the real-world parameters coincide with the simulated ones. Also, it requires the use of advanced algorithms to characterize the environment (e.g., speed, Rician K factor, line of sight (LOS) correlation, etc.).

An alternative approach is to calculate this margin in an *online* manner, exploiting only the usual message exchange between transmitters and receivers, thus avoiding the use of unnecessarily large pre-defined backoff margins. This approach, common in 3GPP systems [7, 8], has also been proposed for satellite communications [6],

In general, the margins will be different if we work with open loop or closed loop CSI. An example arises naturally in the return link of FDD satellite systems : open loop CSI is timely and inaccurate, whereas closed loop CSI is accurate but delayed [9, 10]. Previous work on open loop link adaptation for satellite calculated a margin by simulations [9] or derived it from a statistical characterization of the channel [10]. Also, it was identified that in some cases open loop works better than closed loop, even though a method to switch between both modes has not been proposed yet. A similar idea was presented in [11], where the channel observations on one frequency are used to predict the value of the channel in a different frequency.

In this paper, we propose an automatic mode switching and backoff margin calculator for link adaptation exploiting both open loop and closed loop CSI. We model the return and forward link as two channels with the same LOS components and uncorrelated non-LOS (NLOS). Both open loop and closed loop CSI are weighted depending only on the ACK/NAK exchange, as well as on the observed CSI. The backoff margin and CSI weights are derived as a stochastic programming solution to an optimization problem. As a byproduct, the dynamic margin adaptation in [6] is shown to be a particular case of our method, with fixed CSI weights.

Further, there are some cases where the CSI is not available to perform the MCS selection, or its value is useless because of extremely rapidly time-varying channels. We extend our results to this particular case, and observe that the automatic backoff margin computation plays the role of an estimated SNR from the ACK/NAK exchange.

The remainder of the document is structured as follows: Section 2 presents the system and signal model; Section 3, after introducing the problem statement, addresses the derivation of a number of adaptation algorithms that exploit CSI knowledge, and their refinements to improve their convergence; Section 4 presents an MCS selection algorithm that requires no CSI; Section 5 details the simulation results; finally, Section 6 presents the summary and conclusions.

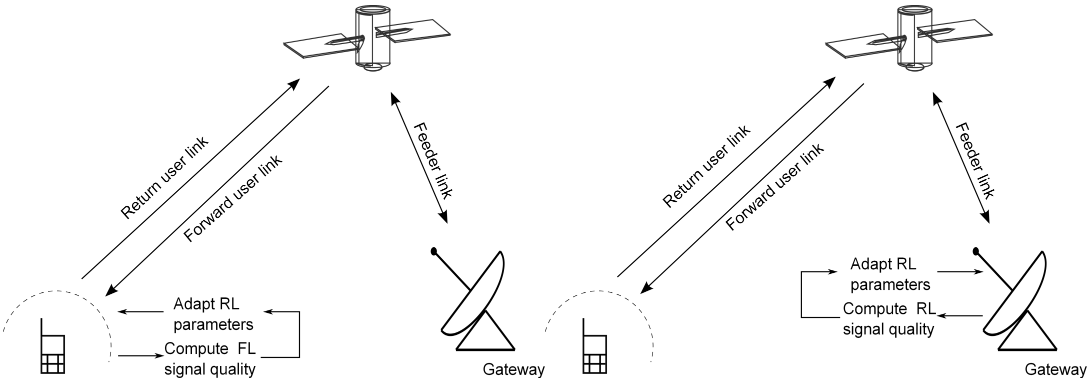

Figure 1. Open-loop (left) against closed-loop (right) adaptation.

2. SYSTEM MODEL

Consider a mobile satellite radio interface operating at the L-band such as that in [12], with the forward link and return link frequency bands centered at $1550\,\mathrm{MHz}$ and $1650\,\mathrm{MHz}$, respectively*. In the following we describe the signal model in detail, along with some key system assumptions.

2.1. Signal model

Through this work we will assume that forward and return link channels experience exactly the same LOS realization, but independent NLOS components with the same power and equal Doppler frequencies†.

Focusing on the return link, whose transmission parameters we seek to adapt, the received symbol at a given time instant i is given by

$$y_i = \sqrt{\mathrm{snr}} \cdot h_i^{\mathrm{rl}} s_i + w_i \tag{1}$$

with s_i the transmitted symbol, h_i^{rl} the channel coefficient and snr the signal to noise ratio; accordingly, w_i is the unit-power noise contribution.

Next we describe the channel model and present some assumptions on the coding used. We shall remark that most of these assumptions are needed for evaluation, but not for design: no particular probability density function (PDF) is assumed for the channel response, whose parameters are considered unknown. This renders a robust adaptation system, oblivious to channel model imperfections.

2.1.1. Channel model For the simulations, we assume that h_i^{rl} follows a Loo distribution [13]: slow variations in the LOS component (*shadowing*) are described by a log-normal distribution, whereas fast fluctuations of the signal amplitude (*fading*) are given by a Rician distribution. The PDF of the signal amplitude at a given time instant is expressed by

$$f_r(x) = \frac{x}{b_0\sqrt{2\pi d_0}} \int_0^{\infty} \frac{1}{z} \exp\left(-\frac{(\log z - \mu)^2}{2d_0} - \frac{x^2+z^2}{2b_0}\right) I_0\left(\frac{x \cdot z}{b_0}\right) \mathrm{d}z \tag{2}$$

where d_0 and μ are the scale parameter and the location parameter of the log-normal distribution, respectively, and b_0 is the variance of the Rician distribution; to determine these parameters we

*More precisely, the frequencies refer to the forward and return user links, or downlink and uplink of the user link. The feeder link, which is operating in a different frequency, is assumed to be transparent.

†This is a simplification, as return and forward link operate in different frequencies. The difference between them, however, is less than 7%.

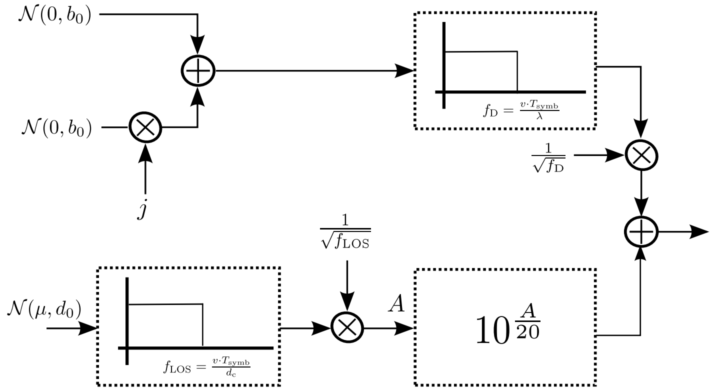

Figure 2. Diagram of the channel generation process. d_0 and μ are the location and scale parameters of the log-normal distribution.

follow the Fontan 3-state model [14]. I_0 denotes the zeroth order modified Bessel function of the first kind.

From an implementation point of view, the LOS component is generated differently from [14], in order to preserve log-normality and ensure stationarity. Starting from i.i.d. Gaussian samples, the correlation properties are introduced before the exponentiation [1, 9, 15] by a low pass filter whose cutoff frequency is given by $f_{\mathrm{LOS}} = v \cdot T_{\mathrm{symb}}/d_{\mathrm{c}}$ where v is the terminal speed, T_{symb} is the symbol period and d_{c} is the measured correlation distance of the LOS component from [16]. We assume that the bandwidth of the system in both forward and return links is of 33.6 KHz, which leads to $T_{\mathrm{symb}} = 1/(33.6 \cdot 10^3)$ s. The NLOS component, on the other hand, is obtained by filtering complex Gaussian samples with a low-pass filter whose (normalized) cutoff frequency is given by the (normalized) Doppler spread $f_D = \nu T_{\mathrm{symb}}/\lambda$, where λ is the wavelength of the carrier signal. This process, as illustrated in Figure 2, applies to both forward (fl) and return link (rl) channels:

$$h_i^{\mathrm{rl}} = h_i^{\mathrm{LOS}} + h_i^{\mathrm{NLOS,rl}}, \quad h_i^{\mathrm{fl}} = h_i^{\mathrm{LOS}} + h_i^{\mathrm{NLOS,fl}}. \tag{3}$$

2.1.2. Transmitted and received symbols The symbols transmitted result from applying forward error correction coding and QPSK constellation mapping to a stream of bits; we consider a finite set of available codes, restricting ourselves to the R20T0.5Q-1B bearer in [12] (see [1]).

Symbols form codewords $\mathbf{s}_i = \left[s_{iN},\, s_{iN+1},\, \ldots,\, s_{(i+1)N-1}\right]$ of constant length N, such that they see the channel samples

$$\mathbf{h}_i^{\mathrm{xl}} \triangleq \left[h_{iN}^{\mathrm{xl}}, h_{iN+1}^{\mathrm{xl}}, \ldots, h_{(i+1)N-1}^{\mathrm{xl}}\right] \tag{4}$$

with $\mathrm{xl} \in \{\mathrm{fl}, \mathrm{rl}\}$. For each sent codeword, we assume that the other end feeds back an ACK if decoding was possible, and a NAK otherwise. We use $N = 2700$, which gives codewords of approximately $80\,\mathrm{ms}$[‡].

If all the symbols in a codeword undergo the same SNR, then it can be readily established whether decoding is successful or not for a given SNR if the corresponding MCS performance is characterized. However, the long duration of the codewords in the case under study disregard metrics such as the average SNR of the time selective channel realization. In general, the average SNR (possibly estimated from pilot symbols scattered through the codeword) is a poor indicator, as very different channel realizations could share the same value. We have used instead an *effective SNR* metric [17]:

[‡]This duration is not necessarily supported by the R20T0.5Q-1B bearer in [12]. A study of the impact of the length of the frames has been left out of this study. Block headers, or similar forms of overhead, are neglected.

$$\gamma^{\mathrm{xl}}_{\mathrm{eff},i} \triangleq \Theta^{-1}\left(\frac{1}{N}\sum_{k=iN}^{(i+1)N-1}\Theta\left(\mathrm{snr}\cdot\left|h^{\mathrm{xl}}_{k}\right|^{2}\right)\right). \tag{5}$$

This represents the SNR of an additive white Gaussian noise channel with the same mutual information as the faded channel $\mathbf{h}_i^{\mathrm{xl}}$, and with $\Theta(\gamma)$ the mutual information over a Gaussian channel with SNR γ and inputs restricted to a certain constellation $\{X_1, \ldots, X_L\}$

$$\Theta(\gamma) = \log_2 L - \frac{1}{L}\sum_{\ell=1}^{L}\mathbb{E}\left[\log_2\left(\sum_{k=1}^{L} e^{-\frac{|X_\ell - X_k + w|^2 - |w|^2}{1/\gamma}}\right)\right] \tag{6}$$

where the expectation is over w and $w \sim \mathcal{CN}(0, 1/\gamma)$.

By using this metric, we assume that the transmission of the i-th codeword fails when $\gamma_{\mathrm{eff},i}$ is below the threshold SNR of the MCS used, and that it succeeds otherwise. Defining $\epsilon_i \in \{0,1\}$ as the error event of the i-th codeword, then

$$\epsilon_i = \begin{cases} 1 & \text{if } \gamma_{\mathrm{eff},i} < \gamma_{\mathrm{th}} \\ 0 & \text{otherwise.} \end{cases} \tag{7}$$

The γ_{th} values are calculated as $\gamma_{\mathrm{th}} = \Theta^{-1}(r)$, with r the spectral efficiency of each MCS.

Remark The use of the effective SNR is just a way of abstracting from the physical layer and reducing the simulation time. However, this channel metric is not instrumental for the algorithms developed in this paper and their subsequent performance, and same derivations would apply with physical layer simulations.

3. MCS SELECTION WITH CSI

3.1. Problem statement

The proposed adaptation method exploits both feedback from the receiver and direct SNR measurements in the forward link. We consider two types of feedback: first, the acknowledgement of the correct decoding of the $(i-d)$-th codeword, so that $\epsilon_0, \ldots, \epsilon_{i-d}$ are available at the transmitter at time instant i, with d the feedback delay; second, a channel quality indicator (CQI) generated from estimates of the channel quality in time instant $i-d$. Our CQI will be the index of the highest MCS supported by channel $\mathbf{h}_i^{\mathrm{rl}}$, i.e., $\mathrm{CQI}_i = \arg\max_j \left[j|E\left(j, \mathbf{h}_i^{\mathrm{rl}}\right) = 0\right]$, where $E\left(j, \mathbf{h}_i^{\mathrm{rl}}\right)$ denotes the error probability when using the MCS of index j in channel $\mathbf{h}_i^{\mathrm{rl}}$. If no MCS is supported, then $\mathrm{CQI}_i = 1$.

The CQI value can be obtained from the effective SNR through a function, Π. The function $\Pi(\mathrm{SNR})$ is an LUT that maps SNR intervals to CQI values. Throughout the paper, we assume that the SNR values are in decibels for convenience. For M MCS values, the function Π can be parametrized by $M-1$ thresholds t_j, $j = 1, \ldots, M-1$, such that $\Pi(\mathrm{SNR}) = j \iff t_{j-1} \leq \mathrm{SNR} < t_j$, where the higher and lower thresholds are defined as $t_0 = -\infty$ and $t_M = +\infty$. The function Π is usually referred to as *inner loop* for link adaptation, and we assume the thresholds to be the γ_{th} values for each MCS[§]. If perfect SNR information was available at the transmitter, the link adaptation procedure would be trivial for a calibrated receiver. In practice, however, this information may not be available, so a correction has to be made to the estimated SNR value.

We define the function $\amalg$ as a function that maps MCS indexes to SNR values, such that $\Pi(\amalg(j)) = j$. For example, a function that maps every MCS index to its SNR threshold γ_{th} meets this requirement, and is the one we will use throughout the paper. The objective of $\amalg$ is to map

[§]Note that the γ_{th} for the first MCS is not used as a threshold.

DOI: 10.1002/sat

CQI to SNR values. We also define $\mathrm{SNR}_i^{\mathrm{cl}} \triangleq \Pi\left(\mathrm{CQI}_{i-d}\right)$ as the SNR that the transmit side gets to know about the received quality d frames earlier in closed loop mode. Note that $\mathrm{SNR}_i^{\mathrm{cl}}$ denotes an estimate of the effective SNR performed in time instant $i-d$, but used at the terminal in instant i. In absence of feedback delay ($d=0$), channel estimation error and other impairments, the optimal MCS selection would be $m_i = \Pi\left(\Pi\left(\mathrm{CQI}_i\right)\right) = \mathrm{CQI}_i$. A common practice to accommodate these impairments is the application of margins on the received CQI value, so

$$m_i = \Pi\left(\mathrm{SNR}_i^{\mathrm{cl}} + c^{\mathrm{cl}}\right) \tag{8}$$

with c^{cl} the SNR margin in dB. A possible approach to select c is by means of an LUT that stores values of c for different scenarios, where parameters like channel distribution, Doppler, detection complexity, etc. have to be taken into account. This approach has some drawbacks that limit its application to practical settings. First, filling the LUT requires running exhaustive simulations under many different settings to be applicable to practical scenarios, and its behavior will be unpredictable under conditions that differ from the stored ones. Second, the receiver has to estimate the required parameters, which can be computationally expensive, and errors in the estimation of these parameters might lead to unexpected behavior. Thus, an adaptive method to adjust c^{cl} is required in many cases. An adaptation of c^{cl} based on ACK/NAK reception was proposed in [7], and applied to the satellite scenario in [6].

On top of the feedback information, the terminal is also observing the channel in the forward link. If the duplexing scheme was TDD, the terminal might gain access to timely and accurate CSI just by measuring the forward link channel. This sort of CSI is called *open loop CSI*. In our setting, duplexing is performed by means of frequency separation, so this assumption does not hold. Under our model, however, there is some degree of correlation between the forward and return link, as the LOS component is the same for both links. Therefore, depending on the scenario, the accuracy of the open loop CSI will vary. Let us define $\mathrm{SNR}_i^{\mathrm{ol}}$ as the most recent SNR estimation on the forward link. We assume that this SNR estimation is perfect, and equal to the effective SNR of the previous codeword, i.e., $\mathrm{SNR}_i^{\mathrm{ol}} = \gamma_{\mathrm{eff},i-1}^{\mathrm{fl}}$. This assumption does not affect the design of the method, and is made for the sole purpose of simplifying the simulations. We might think of performing a similar adaptation as in the closed loop case (8)

$$m_i = \Pi\left(\mathrm{SNR}_i^{\mathrm{ol}} + c^{\mathrm{ol}}\right). \tag{9}$$

Once again, the margin c^{ol} should be obtained adaptively or by means of an LUT. In Figure 3 we show a diagram containing the main variables of the system model.

A further question is how to determine the scenarios for which the use of (8) or (9) is more appropriate. It is expected that in scenarios with relatively low speed or strong multipath the closed loop approach would perform better, while strong LOS and moderate speed scenarios are more suitable for the open loop one. As mentioned earlier, a possible approach is to perform parameter estimation (speed, multipath, etc.) and obtain the optimum strategy from an LUT, which had to be previously filled according to exhaustive simulation results. Alternatively, we present next an adaptive approach which avoids this cumbersome procedure and provides robustness by relying solely on the feedback of CQI and ACK/NAK, as well as on the open loop SNR estimation.

3.2. *Adaptive CSI balancing*

A key observation in (8)-(9) is that they can be jointly described by

$$m_i = \Pi\left(\xi^{\mathrm{ol}}\mathrm{SNR}_i^{\mathrm{ol}} + \xi^{\mathrm{cl}}\mathrm{SNR}_i^{\mathrm{cl}} + c\right). \tag{10}$$

If we set $\xi^{\mathrm{ol}}=0$, $\xi^{\mathrm{cl}}=1$ (10) boils down to (8), and $\xi^{\mathrm{cl}}=0$, $\xi^{\mathrm{ol}}=1$ leads to (9). Note that (10) includes any affine combination of $\mathrm{SNR}^{\mathrm{ol}}$ and $\mathrm{SNR}^{\mathrm{cl}}$, so it generalizes the open loop and closed loop strategies in a dual setting. We now derive an adaptation method for general values of ξ^{cl} and ξ^{ol}; in Section 3.3, we will introduce a more specific formulation if their sum is constrained to be one, $\xi^{\mathrm{cl}}+\xi^{\mathrm{ol}}=1$. For simplicity, we denote $\mathbf{SNR}_i \triangleq \left[\mathrm{SNR}_i^{\mathrm{cl}}\ \mathrm{SNR}_i^{\mathrm{ol}}\right]^T$ and $\boldsymbol{\xi} \triangleq \left[\xi^{\mathrm{cl}}\ \xi^{\mathrm{ol}}\right]^T$;

DOI: 10.1002/sat

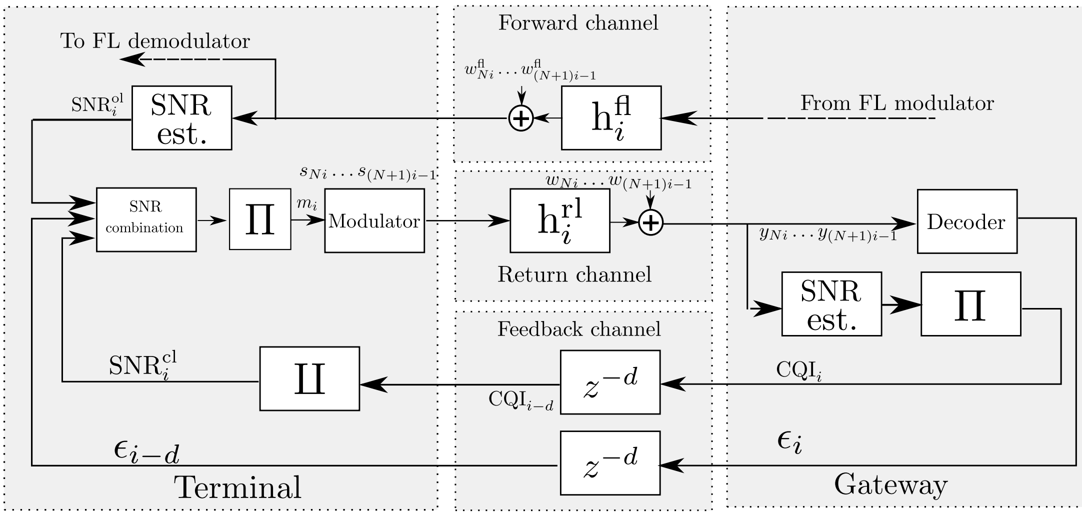

Figure 3. Diagram of the information exchange and link adaptation procedure. The receiver selects the MCS by indexing a LUT with a value obtained by combining the open loop and closed loop SNR. The SNR combination also takes into account the ACK/NAK information to adjust the weights or offsets.

the derivations from now on could be generalized for vectors $\mathbf{SNR}$ and $\boldsymbol{\xi}$ of any size so that, for example, channel prediction can be accommodated within this framework.

Following a similar approach as [18, 19], we state the problem of finding the margin c and SNR balancing weights $\boldsymbol{\xi}$ such that the frame error rate (FER) converges to a fixed *target FER* p_0. Note that we are using the term frame to refer to the physical layer unit containing a codeword encoded with a given MCS, which can change from one frame to the next following the exposed scheme in (10). The required values in this expression can be obtained as the solution to the following optimization problem

$$\min_{c,\boldsymbol{\xi}} J(c,\boldsymbol{\xi}) = |\mathbb{E}[\epsilon] - p_0|^2. \tag{11}$$

It can be observed that (11) does not have any optimality properties in terms of throughput, but just sets the mean packet error rate to the desired value p_0. In practice, nevertheless, it is expected that high SNR values will lead to the use of higher rate MCS to meet the target FER p_0, so the throughput is implicitly increased. Problem (11) can be solved by performing a gradient descent on $J(c,\boldsymbol{\xi})$. The gradient of $J(c,\boldsymbol{\xi})$ can be worked out as

$$\nabla J(c,\boldsymbol{\xi}) = 2\left(\mathbb{E}[\epsilon] - p_0\right)\nabla\mathbb{E}[\epsilon]. \tag{12}$$

A gradient descent iteration reads as

$$\begin{bmatrix} c_{i+1} \\ \boldsymbol{\xi}_{i+1} \end{bmatrix} = \begin{bmatrix} c_i \\ \boldsymbol{\xi}_i \end{bmatrix} - \mu_i \cdot \nabla\, J(c,\boldsymbol{\xi})|_{c_i,\boldsymbol{\xi}_i}. \tag{13}$$

Obtaining a numerical expression for the gradient $J(c,\boldsymbol{\xi})|$ is not possible; the expectation of ϵ

$$\mathbb{E}[\epsilon] = \sum_{\mathrm{CQI}=1}^{M} p(\mathrm{CQI}) \int_{\mathbb{C}^N} E\left(\Pi\left(\amalg(\mathrm{CQI}) + c\right), \mathbf{h}\right) f(\mathbf{h}|\mathrm{CQI})\, \mathrm{d}\mathbf{h} \tag{14}$$

depends on the PDF of the channel, which we assume unknown at the transmitter, and which could even change over time; note that $f(\mathbf{h}|\mathrm{CQI})$ represents the density function of experiencing $\mathbf{h}$ in the current slot given CQI in the previous slot. Instead, we propose a stochastic gradient approach, where the expectations are substituted by instantaneous observations.

Let us define

$$\Omega \triangleq \boldsymbol{\xi}^T \mathbf{SNR} + c \tag{15}$$

DOI: 10.1002/sat

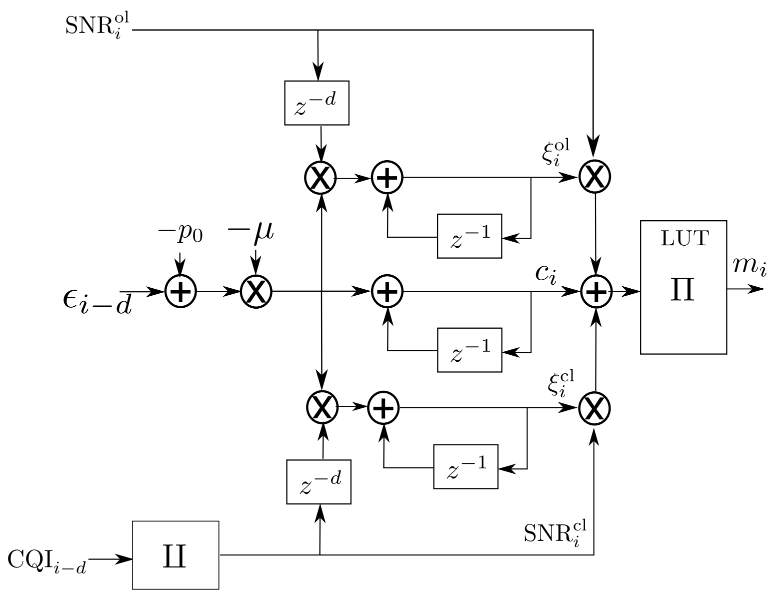

Figure 4. Diagram of the dual adaptation scheme employing both open and closed loop SNR values.

as the indicator SNR with which the MCS m_i is selected in (10). Ω is a function of c and $\boldsymbol{\xi}$ whose gradient is trivial to compute, so that applying the chain rule of differentiation in (12) we arrive at

$$\begin{aligned} \nabla J(c, \boldsymbol{\xi}) &= 2\left(\mathbb{E}\left[\epsilon\right] - p_0\right) \nabla \mathbb{E}\left[\epsilon\right] \\ &= 2\left(\mathbb{E}\left[\epsilon\right] - p_0\right) \mathbb{E}\left[\frac{\partial \epsilon}{\partial \Omega} \nabla \Omega\right] \\ &= 2\mathbb{E}\left[\frac{\partial \epsilon}{\partial \Omega}\right] \left(\mathbb{E}\left[\epsilon\right] - p_0\right) \begin{bmatrix} 1 \\ \mathbf{SNR} \end{bmatrix}. \end{aligned} \tag{16}$$

Following the stochastic gradient approach, we substitute $\mathbb{E}\left[\epsilon\right]$ by the instantaneous value ϵ_{i-d}; also, and since $2\partial\epsilon/\partial\Omega$ is positive¶, we embed $2\mathbb{E}\left[\partial\epsilon/\partial\Omega\right]$ into the positive adaptation constant μ_i. The resulting expression for the update of c and $\boldsymbol{\xi}$ reads as (see Figure 4)

$$\begin{bmatrix} c_{i+1} \\ \boldsymbol{\xi}_{i+1} \end{bmatrix} = \begin{bmatrix} c_i \\ \boldsymbol{\xi}_i \end{bmatrix} - \mu\left(\epsilon_{i-d} - p_0\right) \begin{bmatrix} 1 \\ \mathbf{SNR}_{i-d} \end{bmatrix} \tag{17}$$

where we have removed the dependence of μ with time, so we are using a constant stepsize. We will refer to this as dual or hybrid adaptation since both open and closed loop SNR values are used. We shall notice that, in time instant i, the last received feedback is the one corresponding to the information transmitted in time $i-d$. The SNR values used for adaptation in (17) have to be the ones used for the MCS selection of the packet the ACK/NAK is referred to. Thus, if the transmitter knows the delay introduced by the channel, then a delay of z^{-d} has to be introduced in the adaptation algorithm, as shown in Figure 4. On the other hand, if the delay value is not known or is variable (in case of ACK/NAK grouping, for example), then the transmitter should store the SNR values used for adaptation of every packet, indexed by a packet ID; when the ACK/NAK for a packet ID is received, the parameter update would be performed by recovering the corresponding SNR values from memory. Note that the closed loop SNR value SNR$_i^{\mathrm{cl}}$ used for MCS selection is the one generated by CQI$_{i-d}$, but the one used for the adaptation of ξ_i^{cl} is SNR$_{i-d}^{\mathrm{cl}}$, which is generated by CQI$_{i-2d}$.

¶This can be proved by writing the probability of error, averaged over all channel states, in integral form, and using the assumption that for a channel state, the probability of error is higher for higher MCS. Higher values of Ω lead to higher MCS values, which increase the probability of error.

DOI: 10.1002/sat

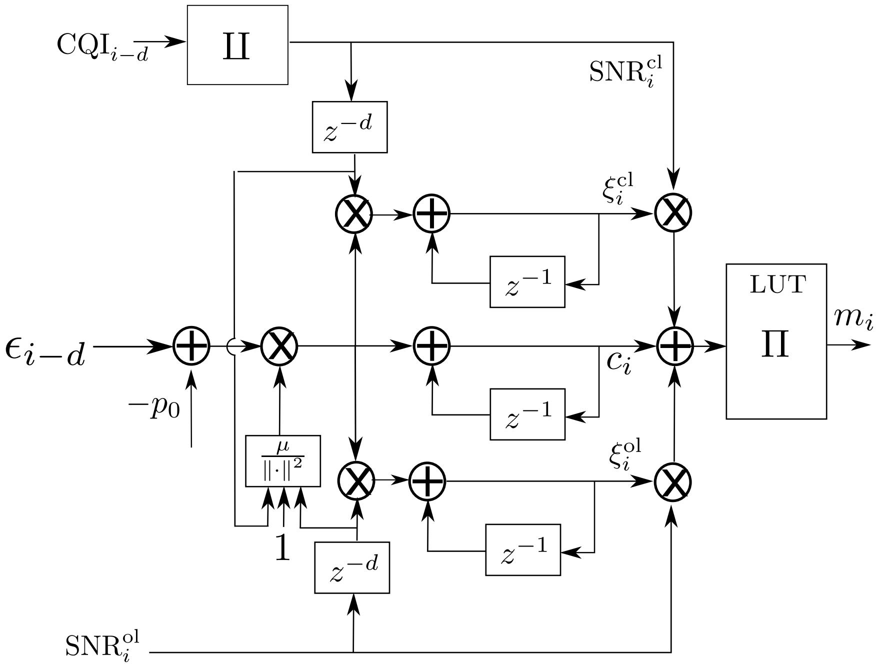

Figure 5. Diagram of NLMS adaptation

Remark The adaptive margin algorithm proposed in [6, 7] is equivalent to the adaptation of c in (17). This adaptation is also the one described in [18]. More precisely, the algorithm for update described in [6, 7] is

$$c_{i+1} = \begin{cases} c_i + \delta_{\mathrm{up}} & \text{if } \epsilon_{i-d} = 0 \\ c_i - \delta_{\mathrm{down}} & \text{if } \epsilon_{i-d} = 1 \end{cases} \tag{18}$$

with δ_{up} and δ_{down} values such that‖

$$\delta_{\mathrm{down}} = \delta_{\mathrm{up}} \frac{p_0}{1 - p_0}. \tag{19}$$

It can be seen that (17) and (18) describe the same adaptation, provided that $\delta_{\mathrm{up}} = \mu p_0$ and $\delta_{\mathrm{down}} = \mu\,(1 - p_0)$.

3.3. Convergence enhancements

Simulations showed that the adaptation method described by (17) offers a noisy behavior in convergence, thus needing small values of μ; this, in turn, decreases the convergence speed dramatically. We now note that (17) resembles a least mean squares (LMS) adaptation with input $[1\ \mathbf{SNR}_{i-d}]^T$ and error $\epsilon_{i-d} - p_0$. Normalized LMS (NLMS) [20] is well known to outperform LMS in convergence speed. If the step-size is normalized in (17), the NLMS-like version reads as

$$\begin{bmatrix} c_{i+1} \\ \boldsymbol{\xi}_{i+1} \end{bmatrix} = \begin{bmatrix} c_i \\ \boldsymbol{\xi}_i \end{bmatrix} - \frac{\mu}{1 + \|\mathbf{SNR}_{i-d}\|^2} \left(\epsilon_{i-d} - p_0\right) \begin{bmatrix} 1 \\ \mathbf{SNR}_{i-d} \end{bmatrix}. \tag{20}$$

A block diagram of this NLMS adaptation is shown in Figure 5. It has been further observed that the NLMS adaptation offers a good convergence performance for the terms ξ, but not for the margin c, since the corrections to this term are smaller in absolute value than those for ξ (because SNR$^{\mathrm{ol}}$ and

‖In [6] the steps are selected to meet $\delta_{\mathrm{down}} = \delta_{\mathrm{up}} p_0$ instead of (19). Both formulations, however, are equivalent for low values of p_0.

$\mathrm{SNR}^{\mathrm{cl}}$ are usually larger than 1). To overcome this problem, we propose an alternative formulation that increases the speed of convergence of c

$$\begin{bmatrix} c_{i+1} \\ \boldsymbol{\xi}_{i+1} \end{bmatrix} = \begin{bmatrix} c_i \\ \boldsymbol{\xi}_i \end{bmatrix} - \frac{\mu}{\theta^2 + \|\mathbf{SNR}_{i-d}\|^2} (\epsilon_{i-d} - p_0) \begin{bmatrix} \theta \\ \mathbf{SNR}_{i-d} \end{bmatrix}. \tag{21}$$

We also performed experiments with only one degree of freedom for the SNR weights. In this case, we defined the MCS selection rule as

$$m_i = \Pi\left(\left(1 - \xi^{\mathrm{cl}}\right) \mathrm{SNR}_i^{\mathrm{ol}} + \xi^{\mathrm{cl}} \mathrm{SNR}_i^{\mathrm{cl}} + c\right), \tag{22}$$

and the corresponding adaptation rule as

$$\begin{bmatrix} c_{i+1} \\ \xi_{i+1}^{\mathrm{cl}} \end{bmatrix} = \begin{bmatrix} c_i \\ \xi_i^{\mathrm{cl}} \end{bmatrix} - \frac{\mu}{\theta^2 + \left(\mathrm{SNR}_{i-d}^{\mathrm{cl}} - \mathrm{SNR}_{i-d}^{\mathrm{ol}}\right)^2} \times \\ (\epsilon_{i-d} - p_0) \begin{bmatrix} \theta \\ \mathrm{SNR}_{i-d}^{\mathrm{cl}} - \mathrm{SNR}_{i-d}^{\mathrm{ol}} \end{bmatrix}. \tag{23}$$

The convergence study of the previous algorithms is quite involved. In Section 4.2 we characterize the evolution of the expectation of the margin c_i when the SNR weights are set to zero as particular case. Simulation results in Section 5 will be shown as support evidence for the convergence in the general case.

4. MCS SELECTION WITHOUT CSI

The algorithms described in the previous section depend on some information exchange between the media access control (MAC) layer and the physical layer, as the MAC layer selects the MCS based on some sort of SNR information (open loop or closed loop), which is obtained from the physical layer. In many cases, such information exchange might not be possible because of system constraints, or simply for hardware simplicity. Also, in some cases the SNR information at the MAC layer would be completely useless (e.g. very high speed scenario for closed loop, or channel incorrelation for open loop). In this section, we present a simple algorithm that performs rate adaptation based only on ACK/NAK information, always available at the MAC layer. We derive this algorithm following a similar approach as in previous sections, and establish connections with classical link adaptation algorithms.

4.1. Automatic rate fallback with memory

Automatic Rate Fallback (ARF) was one of the first link adaptation algorithms for wireless local area networks (WLAN) [21], and has been widely used in industry due to its simplicity. Although different variants of this algorithm exist [22], the basic procedure is as follows:

1. Initialize the algorithm with the selection of an arbitrary MCS.
2. If N_{up} ACK are received consecutively, increase one MCS (if possible).
3. If N_{down} NAK are received consecutively, decrease one MCS (if possible).

Although this simple algorithm does not even require a LUT, we can write ARF as an LUT-based adaptation algorithm using a counter c_i, such that the counter in time instant $i+1$ is

$$c_{i+1} = \begin{cases} \max\{1, c_i - 1\} & \text{if } e_i = e_{i-1} = \ldots = e_{i-N_{\mathrm{down}}+1} = 1 \text{ and } c_i = \ldots = c_{i-N_{\mathrm{down}}+1} \\ \min\{M, c_i + 1\} & \text{if } e_i = e_{i-1} = \ldots = e_{i-N_{\mathrm{up}}+1} = 0 \text{ and } c_i = \ldots = c_{i-N_{\mathrm{up}}+1} \\ c_i & \text{otherwise} \end{cases} \tag{24}$$

DOI: 10.1002/sat

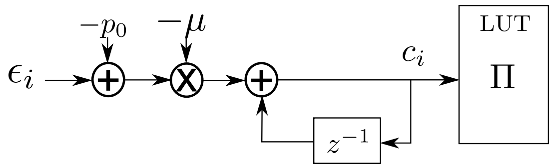

Figure 6. Block diagram of ARF-M.

with the MCS selection rule given by $m_i = \Pi\left(\Pi\left(c_i\right)\right)$.

One of the main problems of ARF is the difficulty to set a target FER. In general, we cannot fix a target FER just by modifying N_{up} and N_{down}, so the selection of N_{up} and N_{down} is heuristic. We propose a modification to ARF to be able to set a target FER, so different QoS can be provided depending on the requirements. Unlike ARF, we derive these algorithms by trying to fix a target FER in some optimal way. We divide the adaptation algorithm in two different parts: an outer loop, that calculates a variable c_i in each instant, and an inner loop, that selects the MCS based on the LUT Π. The variable c_i represents an estimated or tentative SNR value that will be used to index the LUT. Therefore, the selected MCS in time instant i is $\Pi\left(c_i\right)$, and the associated error probability $E\left(\Pi\left(c_i\right), \mathbf{h}_i^{\text{rl}}\right)$. As we will see, we find a strong connection between the MCS c_i and the margin c_i in the adaptation recursion (17).

Similarly to (11), we state our optimization problem as

$$\text{minimize } J\left(c\right) = \left|\mathbb{E}[\epsilon] - p_0\right|^2 \tag{25}$$

where the optimization variable is c, the optimum *estimated SNR* value. Note that $\mathbb{E}[\epsilon]$ can be written as a function of c as

$$\mathbb{E}[\epsilon] = \int_{\mathbb{C}^N} E\left(\Pi(c), \mathbf{h}\right) p(\mathbf{h}) d\mathbf{h}. \tag{26}$$

Following similar steps to those in (16), we arrive to the following stochastic adaptation rule:

$$c_{i+1} = c_i - \mu_i\left(\epsilon_i - p_0\right). \tag{27}$$

We denominate this algorithm ARF with memory (ARF-M). It can be summarized as follows (see Figure 6):

1. Initialize a counter c_0 to an arbitrary SNR value.
2. Decrement the counter by $\mu_i\left(1 - p_0\right)$ if a NAK is received.
3. Increment the counter by $\mu\left(p_0\right)$ if an ACK is received.
4. Select the MCS for transmission in the i-th slot as $\Pi\left(c_i\right)$.

Remark ARF-M can be thought of a particular case of (17) where $\xi_1 = \xi_2 = 0$.

Although this algorithm resembles ARF, there is a key difference that allows ARF-M to set a target FER regardless of the statistical characterization of the channel: the *memory* that is not present in ARF (where, for example, the ACK counter is reset every time a NAK is received). In the following, we prove some convergence properties of the counter c_k, similarly to [18].

4.2. Mean convergence

First, we need to make some assumptions on the relationship between the error probability and the counter c. Let us denote by $p\left(c\right)$ the error probability when the counter is c. Assume that p is a continuously differentiable function**, with derivative bounded by $\delta_0 < \frac{\partial}{\partial c} p\left(c\right) < \delta_1 \, \forall c$, with $\delta_0 > 0$. Let us denote by $c_\star$ the value†† such that $p\left(c_\star\right) = p_0$.

**This is equivalent to assuming a continuous set of transmission rates instead of a finite set of MCS, such that an increment in c always produces an increment on the transmitted rate and, therefore, a higher error probability.
††As p_0 is a monotonic increasing function, this value is unique.

Theorem 1
If $\mu < 2/\delta_1$, then $|\mathbb{E}[c_i] - c_\star| < \eta^i \, |\mathbb{E}[c_0] - c_\star|$, with $0 < \eta < 1$.

Proof
We can write the expected value of c_{i+1} conditioned on c_i as

$$\mathbb{E}[c_{i+1}|c_i] = c_i - \mu \left(p\left(c_i\right) - p_0\right). \tag{28}$$

Note that, by definition, $p_0 = p\left(c_\star\right)$. By using the mean value theorem, we can find $\tilde{c}$ between c_i and $c_\star$ such that $p\left(c_i\right) - p_0 = p'\left(\tilde{c}\right)\left(c_i - c_\star\right)$. Therefore,

$$\mathbb{E}[c_{i+1}|c_i] - c_\star = \left(c_i - c_\star\right)\left(1 - \mu p'\left(\tilde{c}\right)\right). \tag{29}$$

If we take the expectation over c_i on both sides of the equation, we have that

$$|\mathbb{E}[c_{i+1}] - c_\star| = |\mathbb{E}[c_i] - c_\star| \, |1 - \mu p'\left(\tilde{c}\right)|. \tag{30}$$

Convergence is guaranteed if $|1 - \mu p'\left(\tilde{c}\right)| < 1$ or, equivalently, if $\mu < 2/p'\left(\tilde{c}\right)$. Since the value of the derivative is upper bounded by δ_1, it suffices to choose $\mu < 2/\delta_1$. In such a case,

$$|\mathbb{E}[c_i] - c_\star| < \eta^i \, |\mathbb{E}[c_0] - c_\star| \tag{31}$$

with $\eta = |1 - \mu\delta_1|$. Equivalently, it can be proved that

$$|\mathbb{E}[p\left(c_i\right)] - p_0| < \eta^i \, |\mathbb{E}[p\left(c_0\right)] - p_0|. \tag{32}$$

$\square$

5. SIMULATION RESULTS

We simulated the proposed hybrid method (dual), given by equations (21) and (23), which makes use of both open and closed loop SNR. No significant differences were found when using one or two free parameters to weigh both open and closed loop SNR values, so we plotted at each case the one offering a slightly better performance. For reference we compared the dual method with the use of a unique SNR reference, either open loop or closed loop, together with automatic margin adaptation (ARF-M), given by (18), and which does not use any SNR reference to choose the transmitted MCS. Stepsizes were chosen high enough in all cases so that the prescribed FER value, if feasible, was met within the simulation time. Adaptation was performed with $\theta = 10$ and $\mu = 1$ for the dual scheme. For those algorithms with only margin adaptation, $\mu = 0.1$ was used for ARF-M, and $\mu = 0.01$ for both open and closed loop versions. The parameters were initialized as $c_0 = 0$, $\xi_0^{\mathrm{cl}} = 0.5$, and $\xi_0^{\mathrm{ol}} = 0.5$. We set the feedback delay to $d = 5$ codewords to model the round trip time in a GEO satellite.

Results were extracted for a Loo channel with the parameters of an intermediate tree shadowed environment, initially for state 1 [14]. Three different terminal speeds were simulated: 0.75 Km/h, 12.5 Km/h and 60 Km/h, for a target FER of $p_0 = 0.01$. Average spectral efficiency and FER results were averaged over the transmission of $6 \cdot 10^4$ packets. Spectral efficiency is defined as $\frac{1}{N}\sum_{i=1}^{N}\left(1 - \epsilon_i\right) r_{m_i}$, with r_j the rate of the j-th MCS.

The obtained results are shown in Figures 7-9. The dual method matches the FER constraint in all cases except when the SNR is very low; for very high SNR values the achieved FER is even lower. For the lower speed case, the spectral efficiency is similar to both open and closed loop, outperforming ARF-M, which is not exploiting the information contained in the SNR reference. As the speed increases, the closed loop SNR gets more outdated and does not contribute any value to the adaptation, as can be inferred from its relative behavior with respect to ARF-M. For 12.5 Km/h, the dual method spectral efficiency matches that of the open loop; it is important to remark that the dual method is oblivious to the terminal speed, and no prior information on which SNR

DOI: 10.1002/sat

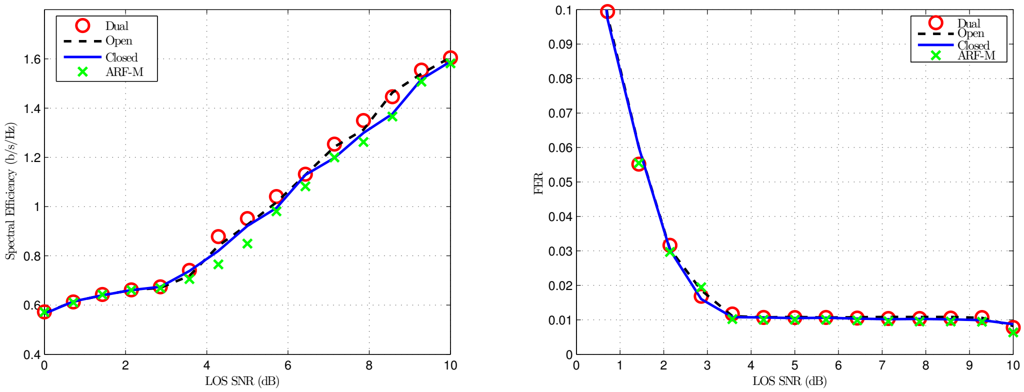

Figure 7. Spectral efficiency and FER for different methods in intermediate tree shadowed environment, state 1, 0.75 Km/h, $p_0 = 0.01$.

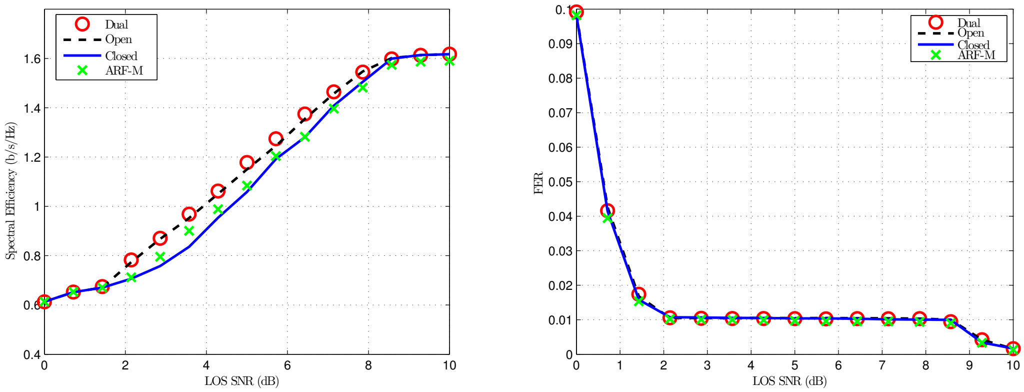

Figure 8. Spectral efficiency and FER for different methods in intermediate tree shadowed environment, state 1, 12.5 Km/h, $p_0 = 0.01$.

reference is more reliable is exploited. For higher speeds even the open loop SNR gets outdated and both dual and ARF-M methods perform similarly, since the CSI can be discarded. Note that the system performance seems to improve with the terminal velocity; this is due to the long duration of the frames (80 ms), which benefit from the diversity effect of the speed, with the variance of the effective SNR decreasing for higher speeds.

In general, the developed scheme is designed such that it fits any situation by adapting the corresponding weights without prior information. In this regard, simulations were also run for multistate scenarios, as illustrated in Figure 10, corresponding to a three-state intermediate tree shadowed scenario [14]. For comparison, previous single state results for the same 60 Km/h speed are also included. The dual method outperforms all other methods, except for a minor degradation with respect to the open loop method in 11 dB. Again, it is important to remark that the dual method main feature lies on its automatic balancing of open loop, closed loop and decoding history information; this requires the adaptation of three weights, which for very specific cases can result in slower convergence. The adaptation algorithms cope with the channel variability by enforcing a prescribed FER value (if feasible); decoding errors are considered to come from insufficient SNR and not from a sporadic large noise event [23, Chapter 3], which is a good approximation for long codes with a steep FER curve such as LDPC or turbo-codes.

We have also tested the impact of interference in the return link; Figure 11 shows the results when the return link suffers interference, in this case yielding a signal to interference ratio equal to

DOI: 10.1002/sat

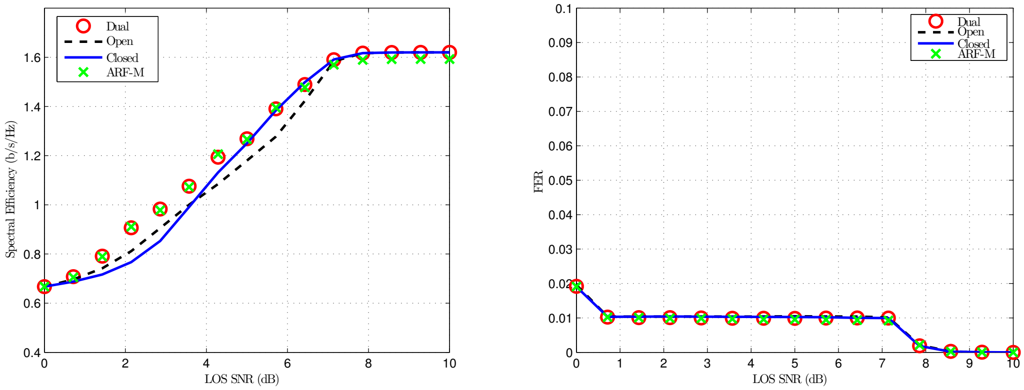

Figure 9. Spectral efficiency and FER for different methods in intermediate tree shadowed environment, state 1, 60 Km/h, $p_0 = 0.01$.

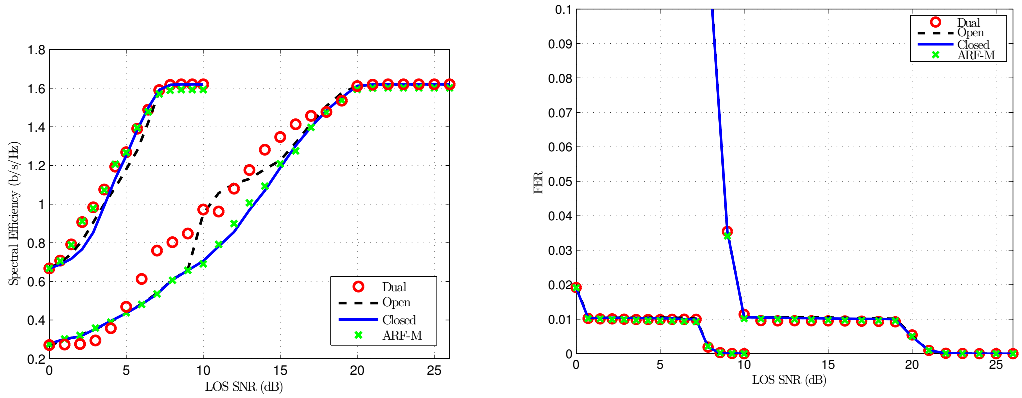

Figure 10. Spectral efficiency and FER for different methods in intermediate tree shadowed environment, multistate, 60 Km/h, $p_0 = 0.01$.

10 dB when the SNR is equal to 6.65 dB, which in turn gives a signal to interference and noise ratio equal to 5 dB. FER target is still achieved and the rate decreases due to the additional degradation. More noticeable, the dual method is still able to accommodate the spoiled reference and offer better performance than ARF-M. Thanks to the adaptive margin, the open loop method is also able to choose appropriate MCS despite the fact that the additional interference will go unnoticed to the open loop SNR.

Despite the reduced number of tested cases, we can conclude that the proposed hybrid scheme is robust against the uncertainty in the channel conditions, and does not need the knowledge of the mobile speed to determine the most appropriate weights of the forward and return link SNR.

6. CONCLUSION

In this paper we presented a method for link adaptation in the return link of satellite communications that exploits open loop and closed loop CSI. The adaptive algorithm is obtained as a stochastic gradient descent of an unconstrained optimization problem. Interestingly, a baseline algorithm arises as a particular case of this optimization problem. The algorithm adapts the weights of each parameter by observing the ACK/NAK sequence and without using any knowledge about the channel evolution other than the estimated SNR provided by each end of the communication. Thus, the estimated SNR

DOI: 10.1002/sat

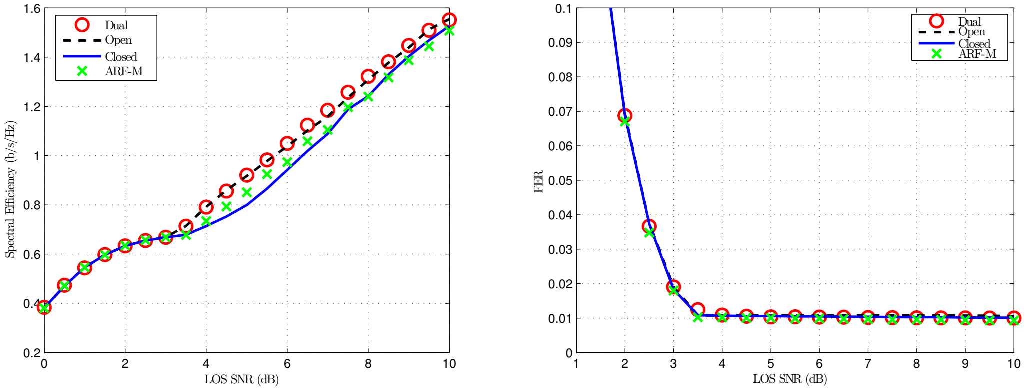

Figure 11. Spectral efficiency and FER for different methods in intermediate tree shadowed environment, state 1, 12.5 Km/h, $p_0 = 0.01$. The interference level is such that the signal to interference ratio in the return link is equal to 10 dB for LOS SNR = 6.65 dB.

by the terminal can prove useful for those cases for which it is significantly correlated with the corresponding channel state when transmitting.

7. ACKNOWLEDGMENT

This work was partially funded by the Spanish Government and the European Regional Development Fund under project TACTICA, by the Spanish Government under projects COMPASS (TEC2013-47020-C2-1-R), by the Galician Regional Government and the European Development Fund under projects Consolidation of Research Units (GRC2013/009), REdTEIC (R2014/037) and AtlantTIC.
The authors would also like to thank Anxo Tato for his help with the simulations.

REFERENCES

1. A. Rico-Alvarino, J. Arnau, and C. Mosquera, "Balancing closed and open loop CSI in mobile satellite link adaptation," in *Proc. ASMS/SPSC*, Livorno, Italy, Sep. 2014, pp. 226–233.
2. T.-S. Yang and A. Duel-Hallen, "Adaptive modulation using outdated samples of another fading channel," in *Proc. WCNC*, vol. 1, Orlando, Florida, USA, Mar. 2002, pp. 477–481.
3. S. Cioni, R. De Gaudenzi, and R. Rinaldo, "Adaptive coding and modulation for the forward link of broadband satellite networks," in *Proc. IEEE GLOBECOM*, vol. 6, San Francisco, CA, Dec. 2003.
4. ——, "Adaptive coding and modulation for the reverse link of broadband satellite networks," in *Proc. IEEE GLOBECOM*, vol. 2, Dallas, TX., Nov. 2004, pp. 1101–1105.
5. ——, "Channel estimation and physical layer adaptation techniques for satellite networks exploiting adaptive coding and modulation," *International Journal of Satellite Communications and Networking*, vol. 26, no. 2, pp. 157–188, 2008.
6. H. Bischl, H. Brandt, T. de Cola, R. De Gaudenzi, E. Eberlein, N. Girault, E. Alberty, S. Lipp, R. Rinaldo, B. Rislow, J. A. Skard, J. Tousch, and G. Ulbricht, "Adaptive coding and modulation for satellite broadband networks: From theory to practice," *International Journal of Satellite Communications and Networking*, vol. 28, no. 2, pp. 59–111, 2010.
7. M. Nakamura, Y. Awad, and S. Vadgama, "Adaptive control of link adaptation for high speed downlink packet access (HSDPA) in W-CDMA," in *Proc. International Symposium on Wireless Personal Multimedia Communications*, vol. 2, Oct. 2002, pp. 382–386.
8. A. Muller and P. Frank, "Cooperative interference prediction for enhanced link adaptation in the 3GPP LTE uplink," in *Proc. IEEE VTC*, Taipei, Taiwan, May 2010.
9. J. Arnau and C. Mosquera, "Open loop adaptive coding and modulation for mobile satellite return links," in *Proc. AIAA ICSSC*, Firenze, Italy, Oct. 2013.
10. J. Arnau, A. Rico-Alvarino, and C. Mosquera, "Adaptive transmission techniques for mobile satellite links," in *Proc. AIAA ICSSC*, Ottawa, Canada, Sep. 2012.
11. T.-S. Yang and A. Duel-Hallen, "Adaptive modulation using outdated samples of another fading channel," in *Proc. IEEE WCNC*, vol. 1, Mar. 2002, pp. 477–481.

12. ETSI TS 102 744, "Satellite component of UMTS (S-UMTS); family SL satellite radio interface," Oct. 2012, draft.
13. C. L. C. Loo, "A statistical model for a land mobile satellite link," *IEEE Trans. Veh. Technol.*, vol. 34, no. 3, pp. 122–127, Aug. 1985.
14. F. Fontan, M. Vazquez-Castro, C. Cabado, J. Garcia, and E. Kubista, "Statistical modeling of the LMS channel," *IEEE Trans. Veh. Technol.*, vol. 50, no. 6, pp. 1549–1567, 2001.
15. D. Arndt, T. Heyn, J. Konig, A. Ihlow, A. Heuberger, R. Prieto-Cerdeira, and E. Eberlein, "Extended two-state narrowband LMS propagation model for S-Band," in *IEEE Int. Symp. Broadband Multimed. Syst. Broadcast.*, Jun. 2012, pp. 1–6.
16. F. Perez-Fontan, M. Vazquez-Castro, S. Buonomo, J. Poiares-Baptista, and B. Arbesser-Rastburg, "S-band LMS propagation channel behaviour for different environments, degrees of shadowing and elevation angles," *IEEE Trans. Broadcast.*, vol. 44, no. 1, pp. 40–76, Mar. 1998.
17. K. Brueninghaus, D. Astely, T. Salzer, S. Visuri, A. Alexiou, S. Karger, and G.-A. Seraji, "Link performance models for system level simulations of broadband radio access systems," in *Proc. IEEE PIMRC*, vol. 4, Berlin, Germany, Sep. 2005, pp. 2306–2311.
18. T. Cui, F. Lu, V. Sethuraman, A. Goteti, S. P. Rao, and P. Subrahmanya, "Throughput optimization in high speed downlink packet access (HSDPA)," *IEEE Trans. Wireless Commun.*, vol. 10, no. 2, pp. 474–483, 2011.
19. S. Nagaraj, "Adaptive rate control with quality of service guarantees in wireless broadband networks," in *Proc. IEEE Globecom Workshops*, Dec. 2013, pp. 519–524.
20. S. Haykin, *Adaptive filter theory*. Prentice Hall, 2002.
21. A. Kamerman and L. Monteban, "WaveLAN-II: a high-performance wireless LAN for the unlicensed band," *Bell Labs Technical Journal*, vol. 2, no. 3, pp. 118–133, 1997. [Online]. Available: http://dx.doi.org/10.1002/bltj.2069
22. Y. Xi, B.-S. Kim, J. bo Wei, and Q. yan Huang, "Adaptive multirate auto rate fallback protocol for IEEE 802.11 WLANs," in *Proc. IEEE MILCOM*, Oct. 2006, pp. 1–7.
23. D. Tse and P. Viswanath, *Fundamentals of Wireless Communications*. Cambridge University Press, 2005.