Multiple lookup table predistortion for adaptive modulation

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Abstract – This paper presents a multiple LUT digital adaptive predistorter based on a Hammerstein model that uses the return channel to feed back information from the receiver, concretely the bit error rate (BER), in order to train and later adapt the specific LUT gains that permit always operating at the best back-off level. This new predistorter architecture is aimed at coping with modern communication standards that use adaptive modulation (such as IEEE 802.11 or IEEE 802.16) and therefore continuously searching the best linear amplification to maximize power efficiency at the time that a certain quality of service (BER) in reception is guaranteed. Simulations provided will show the advantages of this multi-LUT configuration, where in front of different channel conditions, linear and efficient amplification (minimum back-off) is achieved at the time that a certain level of BER at reception is ensured.

Index terms – Lookup tables (LUT), digital adaptive predistortion, Hammerstein models, adaptive modulation systems, peak to average power ratio (PAPR), bit error rate (BER).

I. Introduction

Power Amplifier (PA) linearization is a well known problem extendedly presented in literature, but always open since it has to continuously cope to new communication scenarios where linear amplification is a must and power efficiency is an important figure of merit. Since the former medium and short wave radio transmitters, many linearization techniques have been proposed [1] and significant advances have been reported [2]. The current allowance of high speed digital signal processors (DSP's) not only have revived classical analogue solutions (such as the Kahn's envelope elimination and restoration [EE&R] or the Chireix ones [3]) but also have facilitated new approaches to the linearization problem. Few years ago, the use of digital processors for linearizing PA's was considered a good but disproportionate solution because of the costs and the DSP energy consumption. Nowadays, most of the communication equipment already incorporates some digital processor for mandatory issues within the wireless standards (i.e, coding, interleaving, OFDM…), which can be also used to implement digital-based linearisers avoiding the need for a specific digital device devoted to this function. Among all linearizers, some digital-based linearizers proposed in literature are: Linear amplification using Nonlinear Components (LINC, which is actually a revived Chireix structure) [4], and its variation CALLUM, the EE&R and RF, BB or IF Digital Predistortion. Most of the digital predistorters proposed in the recent past years have been modeled by using memoryless techniques. This PA memoryless model might be an acceptable approximation for narrowband signals (e.g. nearly-constant envelope modulations). However, memoryless predistortion has shown insufficient cancellation performance since new multilevel modulation formats claim for power handling capability and higher baseband bandwidth.

Therefore, for current wideband multilevel modulation formats it is necessary to consider PA memory models. The proposed models used as memory predistortion devices are usually based on Volterra series (or pruned Volterra) [5, 6], memory polynomials [7], Wienner-Hammerstein models [8], or neural networks [9]. Moreover, current communication standards such as IEEE 802.11g, IEEE 802.16, ETSI HiperLAN-2, UMTS or ETSI DVB, look for high spectral efficiency over moderate channel bandwidths (over 20 MHz), by using multilevel modulations, multicarrier or combining both (e.g. M-QAM, π/4 DQPSK, WCDMA, Single Carrier or OFDM). These modulation schemes have information in both amplitude and phase, thus becoming very sensitive to PA nonlinearities. Taking into account that they present high peak to average power ratios (PAPR), significant back-off levels are required for linear amplification, thus penalizing PA's power efficiency. In order to guarantee maximum power efficiency in power amplification, this paper presents a multiple LUT digital adaptive predistorter based on a Hammerstein model (considering memory effects). The advantages of using multiple lookup tables for digital predistortion regarding short-term variations in PA characteristics have been advanced in [10].

The predistorter architecture presented in this paper uses the bit error rate (BER) information coming from the receiver (through the return channel specified in most of modern wireless standards) to design two specific LUT's for each modulation, providing a normal and a safe mode operation. Thus, this architecture permits setting the best back-off level of operation at the time that a certain quality of service (QoS) in reception is achieved.

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In contrast to previous digital predistorters proposals [5-11], this multi-LUT based predistorter solves the problem of coping with different modulation formats, by adaptively calculating the optimum PA + Predistorter gain for operating as close to saturation as possible in order to maximize efficiency.

II. Problem statement

Since some of modern communication standards permit adaptive modulation, that is, changing the modulation format depending on the channel conditions, different PAPR's will be considered for linear amplification. The input back-off can be defined as in [11]:

(1) $$IBO(dB) = P_{in_{SAT}} - P_{in_{AVG}} = PBO + PAPR$$

where $P_{in_{SAT}}$ denotes the input power that corresponds to an output saturated power, $P_{in_{AVG}}$ denotes the input average power level, and PBO stands for the peak back-off, and it is defined as:

(2) $$PBO = -10\log(S)$$

Being S the fraction (value ranging between 0 and 1) of the saturation power that is considered in order to define the maximum input power fed at the PA input to obtain linear amplification:

(3) $$P_{in_{MAX}} = P_{in_{SAT}} \cdot S \qquad (0 < S < 1)$$

So then, considering a communications transmitter that uses different modulation formats presenting different PAPR's it seems reasonable to adapt the input back-off in the PA taking into account the specific modulation used at any time.

In order to adjust the optimum back-off, it is possible to:

– vary the input mean power level for each modulation format. Then, some kind of additional power control will be required;
– alternatively, see eq. (1), maintaining fixed the mean input power, to vary the overall chain gain, composed by the Predistorter plus the PA, thus varying the saturation power level.

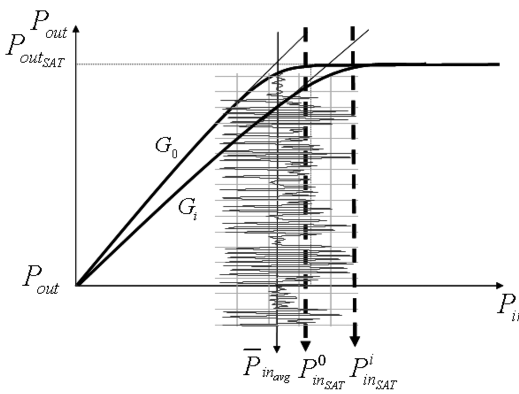

Fig. 1. AM-AM curves of a PA considering different amplification gains.

Therefore, as it is shown in Figure 1, it is possible to set the input back-off level by adjusting the overall Predistorter + PA gain. Moreover, a multilevel modulated carrier only reaches peak envelope power (PEP) occasionally, as it can be observed in Figure 1. Most of the time the modulated carrier is at an average power level significantly lower than the PEP. In order to provide maximum efficient amplification, a certain level of signal clipping will be sometimes desirable and tolerable. So then, the objective of this paper is to propose an adaptive predistorter capable to find the best back-off level in order to obtain power efficient amplification and preserve a specific BER at reception.

III. Predistortion model

Although Volterra series is a general nonlinear model with memory, its predistortion is complex and its real-time implementation difficult. Apart from more complex models such Neural Networks, there are two simple but effective possibilities for describing the predistortion model taking into account memory effects. Those are memory polynomials or Hammerstein (Wiener) models. But, memory polynomial can be seen as a particular configuration of a more general Hammerstein model.

A) Hammerstein model

Hammerstein models are composed by a memoryless nonlinearity followed by a linear time-invariant system, as it is shown in Figure 2. While the Wiener model consists of the same subsystems but connected in the reverse order. The predistorter based on a Hammerstein model can compensate the PA nonlinearities (by means of the memoryless nonlinearity block) as well as the PA frequency-dependent characteristics (by means of the linear time-invariant system). The use of a FIR filter in the linear time invariant block will correspond to a memory polynomial model, as it is described in eq. (4):

Memoryless nonlinearity | LTI (linear time-invariant)

$$x(k) = y_0 \cdot u(k) + y_1 \cdot u^2(k) + \cdots + y^{P-2} \cdot u_{P-1}(k) + y_{P-1} \cdot u^P(k) \longrightarrow H(z) = \frac{\beta_0 + \beta_1 z^{-1} + \cdots + \beta_{N-1} Z^{-1(N-1)}}{1 + \alpha_1 z^{-1} + \cdots + \alpha_D z^{-D}}$$

Fig. 2. Hammerstein model.

(4) $$\tilde{x}(k) = \sum_{p=0}^{P}\sum_{n=0}^{N} b_{np} \cdot y(k-n) \cdot |y(k-n)|^{P}$$

Where $y(n)$ and $\tilde{x}(n)$ are the input and output signals of the predistorter model, while b_{np} $\{n = 1..N; p = 1..P\}$ are complex gains, N and P are the number of delays and the order of the nonlinearity considered in the model respectively.
In this paper we have considered to use an IIR filter in the linear time invariant block, since IIR filters present better resolution than FIR filters at the same filter order, so then, reducing computational load in the DSP

B) Indirect learning of the predistorter
To identify the Hammerstein model parameters, the most common solution is the use of the indirect learning structure (also called translation method [12]), depicted in Figure 3. In a first step, the post-distorter parameters are identified by using the PA output signal and the PA input signal multiplied by a particular linear gain (G^{i}_{linear} , see the PAPR of Fig. 1) whose value will be related to the PAPR of the input signal and thus, to its modulation scheme. Eq. (5) shows the resulting linear amplification derived from the cascade connection of the PA and the post-distorter:

(5) $$F_{post}\left(G\left(x\right)\right) = G^{i}_{linear} \cdot x$$

Once the post-distorter coefficients are estimated, an exact copy of the post-distorter is translated in cascade with the PA, so obtaining the predistorter.
By observing the block diagram in Figure 3, the post-distorter (predistorter) learning process can be defined by the following equations:

(6) $$v(k) = \sum_{p=0}^{P}\gamma_p \cdot y(k) \cdot |y(k)|^{p}$$

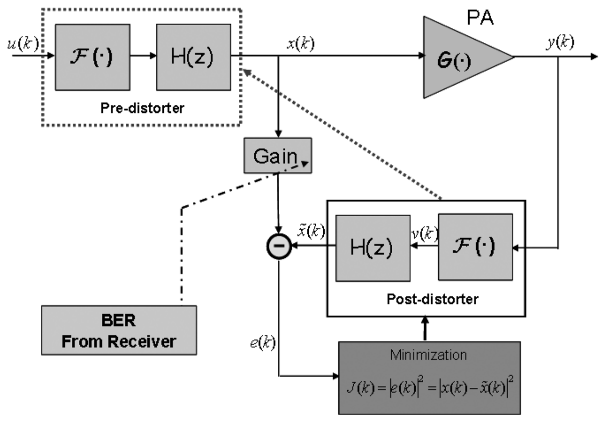

Fig. 3. Indirect learning architecture.

(7) $$\tilde{x}(k) = \sum_{d=1}^{D}\alpha_d \cdot \tilde{x}(k-d) + \sum_{n=0}^{N}\beta_n \cdot v(k-n)$$

Being *y(k)* the PA output and *v(k)* the output of the memoryless non-linear block of the Hammerstein model. *P* is the order of the memoryless polynomial, while *N* and *D* are the general zero/pole order respectively.
By combining eq. (6) and (7) we obtain a closed expression for the predistorter input-output:

(8) $$\tilde{x}(k) = \sum_{d=1}^{D}\alpha_d \cdot \tilde{x}(k-d) + \\ +\sum_{n=0}^{N}\beta_n \cdot \left(\sum_{p=0}^{P}\gamma_p \cdot y(k) \cdot |y(k)|^{p}\right)$$

Rewriting eq. (8) in a more compact matrix notation, it results:

(9) $$\tilde{x}(k) = c_k^H \cdot q_k$$

where $c_k = \begin{bmatrix} d_{01}, d_{02},.., d_{0P}, d_{11}, d_{12},.., d_{1P}.. \\ ..., d_{N1}, d_{N1},.., d_{NP},.., \alpha_1,.., \alpha_D \end{bmatrix}^T$, $d_{np} = \alpha_n \cdot \beta_p$

and $q_k = \begin{bmatrix} y(k),..y(k)|y(k)|^{P}, y(k-1),.., y(k-1)|y(k-1)|^{P}, \\ .., y(k-N),...., y(k-N)|y(k-N)|^{P}, \\ \tilde{x}(k-1), \tilde{x}(k-2),..., \tilde{x}(k-D) \end{bmatrix}^T$

where vectors are noted in bold and matrices are noted in bold and with a hat. The superindex ^{H} denotes Hermitian Transpose.

IV. Identification algorithms

In order to estimate the post-distorter coefficients, the cost function to be minimized (*J(k)*), is defined as the mean square error between the output samples of the post-distorter and the input samples (previously multiplied by the desired linear gain) of the PA, as is shown in eq. (10)

(10) $$e(k) = x(k) - \tilde{x}(k) = x(k) - c_k^H \cdot q_k$$

(11) $$J(k) = |e(k)|^2 = |x(k) - \tilde{x}(k)|^2$$

To minimize this cost function two algorithms are proposed: the Least Mean Square (LMS) algorithm and the Fast-Kalman Filter. Other algorithms such Least Squares or Recursive Least Squares are suitable for training the predistorter, but result more computational complex for the adaptation process in front unexpected changes in the PA characteristics.

A) Least Mean Square (LMS)
The well-known Least Mean Square algorithm is described in eq. (12).

$$c_{k+1} = c_k + \mu \cdot q_k \cdot e(k)^* \quad (12)$$

being *m* the error step (trade-off between speed of convergence and accuracy), and its bounds are:

$$0 < \mu < \frac{2}{Tr\left[q_k \cdot q_k^H\right]} \quad (13)$$

where *Tr[·]* denotes the trace of the data (signal) matrix.

B) Fast-Kalman Filter
Fast-Kalman algorithms [13] use the optimum Kalman filtering technique to adaptively estimate the predistorter coefficients without the need of knowing *a priori* any transition matrix (unlike the conventional Kalman filter). The Fast-Kalman equations describing the algorithm are [13]:

$$c_{k+1} = c_k + h_k \cdot e(k)^* \quad (14)$$

being,

$$h_k = \frac{\overline{\lambda}_{k-1} q_k}{q_k^H \overline{\lambda}_{k-1} q_k + Q_M} \quad (15)$$

where Q_M and $\overline{Q}_P$ are related to the estimation and measure error variance [13]. The $\overline{\lambda}_k$ matrix is recursively updated like:

$$\overline{\lambda}_k = \overline{\lambda}_{k-1} - h_k q_k^H \overline{\lambda}_{k-1} + \overline{Q}_p \quad (16)$$

C) Look-up table (LUT) coefficients
Since real-time adaptation algorithms would require a high speed DSP capable to calculate complex algorithms within a symbol period, the use of pre-trained look-up tables simplifies the DSP computational load and relaxes the adaptation time constants. Therefore, one possible implementation of a Hammerstein based predistorter will consist of the use of LUT's to compensate the memoryless nonlinearities of the PA, followed by an IIR filter (see Fig. 4), to compensate possible memory effects derived from electrical of thermal effects.
But, for dividing the predistorter into a LUT plus a IIR filter, it is necessary to firstly have the Hammerstein parameters separately. Having a look at eq. (12) and/or eq. (14), it is possible to notice how by using the LMS or Fast-Kalman algorithms we obtain the c_k coefficient vector, where $d_{np} = \beta_n \cdot \alpha_p$. To identify gammas and betas separately, it is possible to apply the two stages identification algorithm proposed by Bai in [14], consisting in a singular value decomposition of the $\overline{H}$ matrix described in eq. (17).

$$\overline{H} = \sum_{i=1}^{\min(N,P)} \mu_i \cdot \sigma_i \cdot \nu_i^H = \overline{U}\,\overline{\Theta}\,\overline{V}^H \quad (17)$$

where the $\overline{H}$ matrix is defined as:

$$\overline{\boldsymbol{H}} = \begin{pmatrix} d_{00} & d_{01} & \cdots & d_{0P} \\ d_{10} & d_{11} & & \vdots \\ \vdots & & \ddots & \vdots \\ d_{N0} & d_{N1} & \cdots & d_{NP} \end{pmatrix} = \begin{pmatrix} \beta_0\gamma_0 & \beta_0\gamma_1 & \cdots & \beta_0\gamma_P \\ \beta_1\gamma_0 & \beta_1\gamma_1 & & \vdots \\ \vdots & & \ddots & \vdots \\ \beta_N\gamma_0 & \beta_N\gamma_1 & \cdots & \beta_N\gamma_P \end{pmatrix} \quad (18)$$

being the matrices $\overline{\boldsymbol{U}} = (\mu_1, \mu_2, \cdots \mu_N), \overline{\boldsymbol{V}} = (\nu_1, \nu_2, \cdots \nu_N)$ and where $\mu_i(i = 1,2,\ldots,N), \nu_i(i = 1,2,\ldots,P)$ are N-P-dimensional orthonormal vectors respectively, and
$\sigma_1 \geq \sigma_2 \geq \cdots \sigma_{\min(N,P)} \geq 0$.
Finally, the gammas and betas are estimated as described in eq. (19) and eq. (20).

$$\hat{\beta} = s_\mu \cdot \mu_1 \quad (19)$$

$$\hat{\gamma} = s_\mu \cdot \sigma_1 \cdot \nu_1 \quad (20)$$

where s_u denotes the sign of the first nonzero element of μ_1.
Alternatively, by using the Narendra-Gallman (NG) algorithm [15], based on the estimation of the predistorter coefficients by means of the Least Squares technique, it is possible to separately obtain the alphas, betas and gammas coefficients. The NG algorithm can be perfectly used to synthesize multiple LUT's in the training process, but for later adaptation the LMS or the Fast Kalman algorithms are better fitted since they are simpler and faster.

V. Multiple lookup tables

The block scheme of the multi-LUT based predistorter is shown in Figure 4. It consists of a set of 2 × Q LUT's and their associated IIR filters, being Q the number of modulation schemes considered. Each modulation format has assigned two LUTs with different gains, the normal gain and the safe mode gain, as well as their corresponding filters. This bank of LUT's aims at compensating the PA nonlinear behavior, and IIR filters at compensating the PA memory effects.

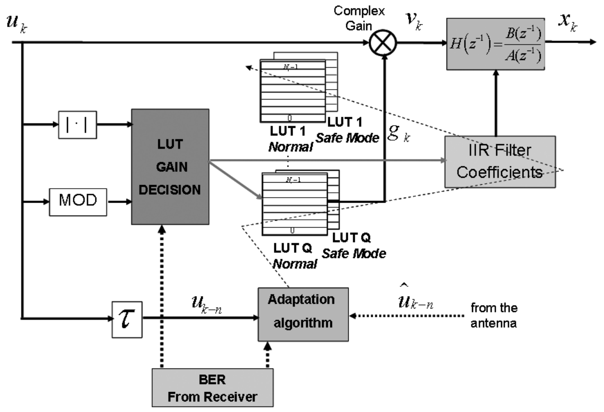

Fig. 4. Structure of an adaptive Multi-LUT based predistorter.

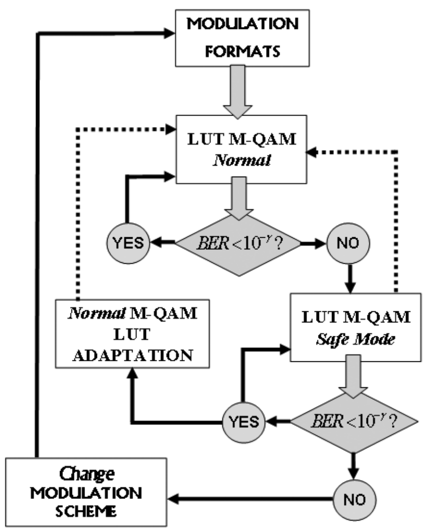

Fig. 5. LUT gain decision algorithm.

The normal gain LUT operates with the minimum necessary back-off that accomplishes BER specifications at reception, so then, aiming at always operating in the most efficient dynamic range. While the safe mode gain LUT provides a significant back-off operation in order to compensate any degradation in the PA characteristics or the channel conditions.

The "LUT Gain Decision" block in Figure 4, performs the LUT gain decision algorithm described in Figure 5. In a first step, taking into account the modulation format of the input signal, a normal gain LUT (with its corresponding filter) is assigned. If the minimum BER required at reception is not guaranteed ($BER > 10^{-\gamma}$), the LUT gain decision switches into the safe mode gain LUT. Then, if the minimum BER is accomplished, starts in parallel (in a different time scale) the adaptation process of the normal gain LUT in order to readjust any possible variation suffered in the PA characteristics. But, if operating with the safe mode gain LUT the desired BER at reception is not accomplished, that means that PA nonlinear behavior does not contribute that much in BER degradation as channel conditions do. Thus the transmitter has to choose a more robust modulation format.

VI. Experimental results

A) Power amplifier model characterization

For the experimental results, we have considered a PA Hammerstein model estimated from modulated input and output data of a class-A PA designed with the Agilent ATF-54143 PHEMT transistor. The obtained coefficients are listed in Table 1, and its static AM-AM curve is shown in Figure 6.

B) Training Process: calculating Multi-LUT Gains

In the training process, four different types of modulation schemes (all of them supported by the IEEE 802.16 standard) filtered by a root raised cosine filter with a roll-off factor of $\alpha = 0.35$ have been considered: QPSK, 16-QAM, 64-QAM and 256-QAM (all Gray constellation ordered). The communications channel is an Additive White Gaussian Noise (AWGN) channel with a signal to noise ratio (SNR) in reception of 10

Tab. 1. PA Hammerstein model coefficients.

	Gammas	Alf=as	Betas
0	–4.42 – 9.16i	–0.098 + 0.00705i	–0.843 – 0.0378i
1	49.0 + 44.43i	0.25444 – 0.00903i	0.21 + 0.00089989i
2	–472.76 – 363.65i	–0.1187 + 0.0129i	–0.0986 + 0.00705i
3	2226.2 + 1513.3i	--	--
4	–5610.1 – 3463.6i	--	--
5	7704.4 + 4383.5i	--	--
6	–5400.7 – 2844.6i	--	--
7	1509.5 + 734.93i	--	--

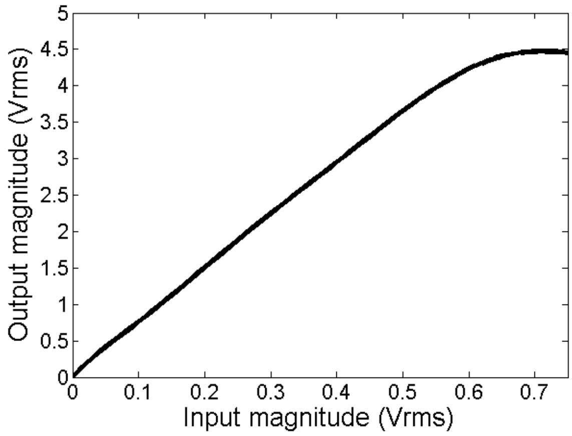

Fig. 6. Power amplifier AM-AM curve (7th order).

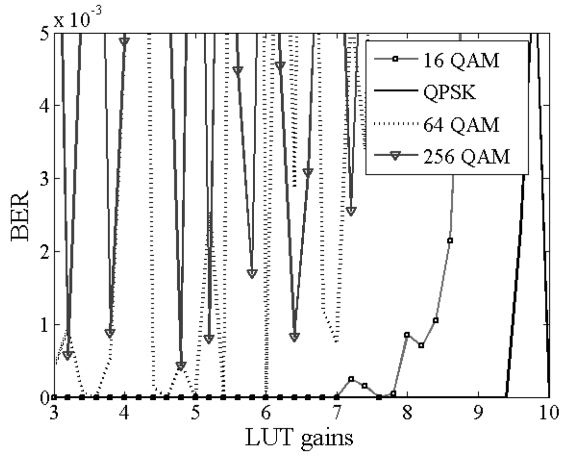

Fig. 8. BER versus LUT Gains (Zoom on the y-axis of Fig. 7).

dB, nor multipath nor Doppler have been considered. Assuming 50 Ω adaptation for the overall system, the 1 dB compression point (see Fig. 6), will approximately correspond to an input amplitude of 0.75 V_{rms}, that is, an input power of 7.5 dBm, while the output saturation power is 23 dBm approximately (corresponding to 4.5 V_{rms}).

The PAPR of the considered modulations can be calculated using eq. (21):

$$(21) \qquad PAPR(dB) = 10 * \log(CF)^2$$

being the crest factor (CF) the ratio of the peak to r.m.s amplitude of a signal, as it is described eq. (22):

$$(22) \qquad CF = \frac{x_{peak}}{\overline{x}}$$

For our particular power amplifier, with an input saturated power of 7.5 dBm, and taking into account a fraction of the saturation power of $S = 0.95$ (see eq. (1), (2) and (3)), what corresponds to a peak back-off of $PBO = 0.22\ dB$, the maximum input power is set at 7.13 dBm. So then, considering the most restrictive PAPR (belonging to the 256 QAM modulation, see Table 2) and by using eq. (1), the minimum recommendable IBO for linear amplification will be $IBO \geq 7.5\ db$. But, by using Multi-LUT predistortion, the mean input power is fixed at 3 dBm, so then considering a general IBO of $IBO = 4.5\ db$, independently of the modulation used.

In order to accomplish BER specifications at reception, all normal and safe mode gain LUT's with their corresponding filters have to be calculated in advanced. Figure 7 shows the Bit Error Rate for different LUT gains and for different modulations schemes, considering an input mean power of 3 dBm, an AWGN channel with SNR = 10 dB and LUT's with 128 entries.

Considering a BER restriction of $BER < 10^{-3}$ (prior to code gain inclusion) and observing Figure 8 (a zoom of

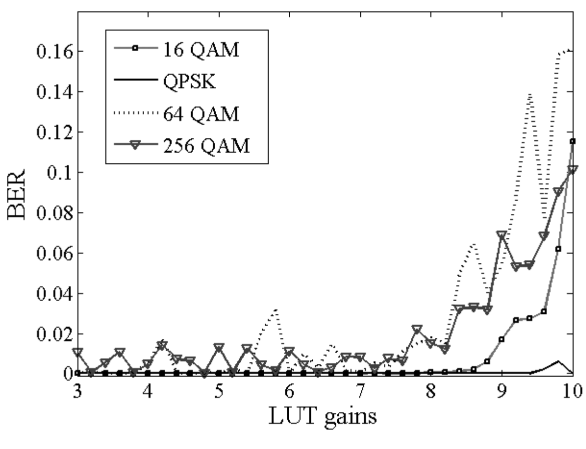

Fig. 7. BER versus LUT Gains (Pin = 3 dBm, LUT's of 128 bins).

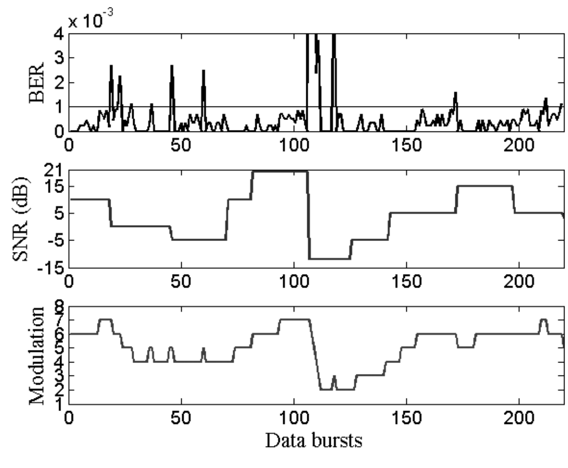

Fig. 9. BER and modulation schemes for different SNR channel conditions.

Tab. 2. Modulation requirements and LUT-Gains results.

Modulation scheme	QPSK	16-QAM	64-QAM	256-QAM
PAPR (roll-off = 0.35)	4.15 dB	6.43 dB	6.97 dB	7.2 dB
IBO	4.37 dB	6.65 d	7.19 Db	7.44 dB
Theoretical required mean input power	3,13 dBm	0.85 dBm	0.31 dBm	0.08 dBm
LUT Gain at Normal and Safe Mode	N: 9.4	N: 7.5	N: 6	N: 4.8
P?? = 3 dBm	SM: 9	SM: 7	SM: 5.4	SM: 3.2

Fig. 7), the LUT-Gains for each modulation are listed in Table 2.

C) Normal process

Figure 9 shows the BER and the different modulation formats for different SNR of the AWGN channel. Modulations 8 and 7 correspond to the 256 QAM normal and safe mode gain LUT's; modulations 6 and 5 correspond to 64 QAM; 4 and 3 to 16 QAM; finally, 2 and 1 to QPSK normal and safe mode gain LUT's respectively.

Looking at Figure 9 it is possible to identify the LUT decision algorithm described in Figure 5. Until efficient amplification is possible the normal gain LUT is preferred, but when channel conditions get worse, if the safe mode gain LUT is not enough, then the modulation format is changed. Note that after adaptation the algorithm retries with a more effective amplification (or modulation format if applies).

VII. Conclusion

In this paper a multi-LUT digital adaptive predistorter capable of supporting different modulation formats at the time that assures high efficient linear amplification by feedbacking the BER information at the receiver has been presented. The design process and basic principles have been reported, as well as simulation results that show its good performance. Among different possibilities for model parameters identification, those showing less computational effort have been here considered, aiming to set up the predistorter algorithm inside the already existent DSP infrastructure in modern communication systems, thus minimizing perturbation to other DSP functionalities.

The main advantage of this multi-LUT predistorter is that even when the dynamic range is adjusted at the best back-off level, there is no penalization in the amplification gain, since it always operates as close to saturation as the specified BER at reception permits.

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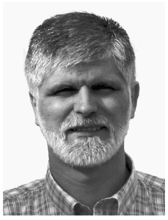

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