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Peak-Power Controlled Digital Predistorters for RF Power Amplifiers

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Abstract—This paper investigates the issue of “predistorter blow-up” i.e., uncontrolled peak expansion caused by the predistorter. To control the peak expansion, an extension of the multistep indirect learning architecture (MS-ILA) is proposed by adding a constraint that describes the allowed peak power of the predistortion signal. The resulting optimization problem is shown to be convex and an optimization method is formulated to solve it.

Measurements on a class-AB power amplifier (PA) using orthogonal frequency division multiplex (OFDM) signals show that the peak control works as intended and prevents the MS-ILA from generating high peaks when the PA is operated in compression. The restriction on the peak power also prevents the performance degradation occurring due to the “blow-up” problem. This makes the proposed controlled MS-ILA a safer option than the standard MS-ILA.

In addition to controlling the peak input power to the PA, using the proposed method it was possible to increase the output power by 1.3 dB while fulfilling requirements of less than 40 dB adjacent channel leakage power ratio (ACLR), compared to the standard five step MS-ILA. Reduced peak power also reduces the requirements on linearity in signal generation, resolution in computations, analog-to-digital and digital-to-analog conversion.

Index Terms—Nonlinear systems, system identification, memory polynomials, power amplifiers, telecommunication, linearization, optimization

I. INTRODUCTION

POWER amplification of radio frequency (RF) signals is still an issue, despite the last years’ advances in power amplifier (PA) design and linearization techniques. There is a trade-off between the linearity and efficiency in PAs [1].

Traditional PAs can be viewed as compressive devices, with a certain amount of memory. The compressive behavior of RF PAs is a nonlinear operation that causes spectral regrowth and constellation distortion compared to the original input signal. The first effect is commonly quantified through the adjacent channel leakage power ratio (ACLR) whereas the second effect is commonly quantified as error vector magnitude (EVM). For telecommunication and broadcasting systems there are

regulatory limits on the amount of distortions. If any of these limits are exceeded, the transmitter cannot be used.

Several methods for correcting these distortions have been proposed. The simplest is backing off the input power to a lower level. Unfortunately, this results in reduced power efficiency. Feedback linearization has been proposed and used but it suffers from limited bandwidth [2], although recent works claim to have overcome this limitation [3]. Feedforward linearization [2] has also been used but it suffers from low power efficiency due to the linear cancellation amplifier. Another method that is widely used is the baseband digital predistortion (DPD) [4]. This can be implemented using look-up-tables (LUT) as in [5], [6] or using behavioral models [4], [7]. DPD has become relatively popular, partly due to its’ relatively good performance and low complexity.

Finding this inverse operation of the PA can be done in a large number of ways: direct training of a look-up table (LUT) over the PA operation [5], model-based predistortion where the model is trained using an iterative method, such as recursive least-squares (RLS), least-mean square or similar methods [7], finding a direct model of the PA behavior and training the predistorter using this model [8], or using the indirect learning architecture (ILA) in [7].

However, for a successful DPD it is also necessary to update the parameters in the case of a model [7], or the LUT entries in case of a LUT-based approach [5], [6]. While the PA is operating in back-off this is relatively easy using the indirect learning architecture (ILA) suggested in [7]. When the PA operates in compression the linearization is achieved by expanding the input signal in a nonlinear fashion. This is the opposite of the compressive PA operation and leads to problems with the very high signal peaks in the input signal to the PA.

For estimating the parameters of the predistorters in the present paper, we focus on the ILA in [7] because it is a simple and straightforward method. The ILA method has been shown to work well to linearize RF PAs [7], [9]–[15]. However, when the PA operates in deep compression, the ILA DPD tends to give predistortion signals that have unreasonable peak-to-average power ratio (PAPR) [14], [15]. There are a number of problems related to these very high signal peaks. The dynamic range of the digital-to-analog converters (DACs) used in the signal generation is not sufficient to cover the full amplitude span with enough amplitude resolution. The driver amplifiers and/or the power amplifier can break due to the high voltages.

This problem has a simple explanation, namely that the PA is compressing the signal. The DPD is the inverse of this

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behavior, i.e., an expansion. In [14], [15] it was observed that the multistep (MS)-ILA results in increased PAPR-values after each step. In [7] it was observed that the signal peaks tend to grow when using the ILA, but the subject was not further pursued. To the knowledge of the authors, the issue of strongly increasing peak powers in the predistortion signal has not been further discussed, other than a general note that DPD alone does not give much improvement in output power for semi-linear PAs, like class-AB [14], [15].

This paper proposes a method that limits the peaks of a predistortion signal to be below a specified value, i.e., input voltage to the PA. This is achieved by simultaneously using the ILA algorithm and putting constraints on the input signal amplitude.

In the field of control theory, the problem of saturating actuators has been studied in some detail, see [16], [17]. This is a problem that is similar to the problem of saturation in the PA and the driver amplifiers. Both are limited in amplitude but can be made to behave linearly up to a given power level. The authors in [16] roughly classify the approaches of solving problems with saturating actuators as being either “... *ad hoc anti-windup schemes*...” or using a systematic method. The method proposed in the current paper is more of an *ad hoc* method in the sense that it takes the existing method of ILA and introduces an extra step to control the saturation.

We show that the proposed approach of peak controlled DPD provides an improvement over published state-of-the-art methods. By limiting the predistorter output, the *blow-up* problem is avoided. Additionally, advantages such as increased output power, lower input and output peak power levels, reduced requirements on the signal generation and signal processing parts of the whole transmitter system also follows.

In the first part of Sec. II, linearization and ILA are reviewed. The peak controlled ILA is then introduced and the resulting problem is shown to belong to the class of convex optimization problems [18] in the second part of Sec. II. The measurement prerequisites are given in Section III. Results measured on a class-AB PA are presented and discussed in Section IV. Conclusions are then given in Section V. Details for the numerical method are given in Appendix A.

II. THEORY

This section first introduces the concept of the ILA originally proposed in [7] for PA linearization, then presents the proposed methods for peak limiting and finally shows the implementation using a primal-dual method.

A. Indirect Learning Architecture

1) *Single-step ILA*: The goal of DPD when applied to an RF PA is to introduce a preinverse block $G_{\text{pre}}(\cdot)$ which linearizes the nonlinear system $K(\cdot)$ (the PA), as in Fig. 1(a). Another similar situation is when one wishes to have a postinverse of a nonlinear system, i.e., the correcting function should be located after the nonlinear system as in Fig. 1(b). A typical application of such postinverses is the correction of analog-to-digital converters [19].

Fig. 1. Operating principles of pre- and postdistorters. In both cases, $x(n)$ is the input signal and $K(\cdot)$ is the nonlinear system to be linearized by either the preinverse $G_{\text{pre}}(\cdot)$ or the postinverse $G_{\text{post}}(\cdot)$. For the predistorter case, $x_{\text{pre}}(n)$ is the predistortion signal, $y_{\text{pre}}(n)$ is the output signal when a predistortion signal is used. For the postdistorter case, $y(n)$ is the output signal of the nonlinear system and $y_{\text{post}}(n)$ is the postdistorted (linearized) output signal.

For nonlinear systems of Volterra type, Schetzen derived the p^{th} order inverse [20] of a nonlinear system. This inverse is simultaneously both the preinverse and the postinverse of a Volterra system, up to the given nonlinear order p [20].

However, in [7] it was noted that the p^{th} order inverse suffers from the drawback of having higher nonlinear orders that are not compensated. The higher order nonlinear terms created by the interconnection of the nonlinear system and the pre- or postinverse are not compensated. This is in the nature of the p^{th} order inverse. Furthermore, the p^{th} order inverse requires access to the direct model of the system in order to perform the inversion. This means that an additional model must be implemented and stored in the data processing part of the system.

Another approach to find a preinverse is to directly identify a preinverse. This can be done either by a nonlinear search directly over the system or by using a model of the direct system as in [8]. However, this requires the analytical or numerical inversion of a nonlinear system, which can be a computationally demanding task.

To solve the above-stated problems, [7] introduced the ILA. The ILA is based on indirectly training a postdistorter and then putting that postdistorter in front of the nonlinear system to act as a predistorter. The idea is based on noting that if the input signal is equal to the output signal (after scaling and synchronization), then the output of the preinverse and the output of the postinverse are equal [7]. This observation is what allows us to use the postdistorter as predistorter.

If the model structure for the pre- and postdistorter is chosen to be linear in the parameters, then the parameter estimation can be carried out by standard linear least-squares methods. This becomes

$$\hat{\eta} = \arg \min_{\eta} \|\mathbf{u} - \mathbf{H}(\mathbf{y})\eta\|_2^2 \quad (1)$$

where $\|\cdot\|$ denotes the standard Euclidean norm, $\mathbf{H}$ is the regression matrix, $\mathbf{u}$ is a vector of input signal samples and $\mathbf{y}$ is a vector of output signal samples.

The predistortion input signal to the PA is then given by

$$\mathbf{u}_{\text{DPD}} = \mathbf{H}(\mathbf{u})\hat{\eta} \quad (2)$$

Let $\mathbf{u}_{\text{DPD},0}$ be a vector of data samples from the input data set $u_0(n)$
 Let $\mathbf{y}_{\text{DPD},0}$ be the vector of measured output samples from the PA when $\mathbf{u}_0$ is the input signal
for $k = 1, 2, \dots$ **do**
 Estimate $\hat{\eta}_k$ by using (1) with $\mathbf{u} = \mathbf{u}_{\text{DPD},k-1}$ and $\mathbf{y} = \mathbf{y}_{\text{DPD},k-1}$
 Compute predistortion signal $\mathbf{u}_{\text{DPD},k}$ by applying (2) with $\mathbf{u} = \mathbf{u}_k$, where $\mathbf{u}_k$ is the vector of data samples for a signal $u_k(n)$, $n = 0, 1, \dots, N_k - 1$
 Transmit $\mathbf{u}_{\text{DPD},k}$ and measure $\mathbf{y}_{\text{DPD},k}$
end for

Fig. 2. Algorithm describing the multistep ILA (MS-ILA).

with $\mathbf{H}(\cdot)$ and $\hat{\eta}$ given as in (1). This method of linearization has been shown to work well in a number of publications [7], [9]–[15].

2) *Multi-step ILA*: Unfortunately, due to the changes in the PA it is not sufficient to identify the predistorter once, but updates of the predistorter parameters are necessary with changes in operating power, temperature, aging, signal characteristics etc. To solve this efficiently, [7] derived a modified recursive least-squares (mRLS) version of the ILA, henceforth named the mRLS-ILA.

An alternative to using the mRLS-ILA for parameter updates is to use the multistep ILA. This is a repeated single-step ILA, henceforth denoted the MS-ILA, which operates according to the algorithm in Fig. 2.

Note that the input signal $u_k(n)$ does not need to be the same signal for all k but can be allowed to change. The number of samples N_k used to estimate the signal can also vary if desired, but it must contain enough information about the amplitude and frequency range that the PA currently is operating in. Strictly formulated, it should contain enough information on the higher order spectra as shown for direct modeling in [21].

This makes it possible to adapt to changes in the system, but also to account for the extrapolation caused by the expansion operation of the DPD. The expansion is treated in detail in the following.

B. Expansion Operation of DPD

In [7] it was observed that the peaks of the predistortion signal tended to increase but the observation was not further investigated in that publication. Instead, in [22] some aspects of changes in signal characteristics were discussed and observed for the p^{th} order inverses. In [14], [15] it was observed that the PAPR of the predistortion signals increased after each step of the MS-ILA. For a robust operation this is not a desirable situation because it could potentially lead to a situation where the expansion increases after each parameter update.

In the first step of the MS-ILA, the signal is slightly compressed upon which the predistorter expands it, thus creating an extrapolation. The signal is then transmitted and the peaks, which now have higher amplitude, are more compressed. To compensate this compression the next step of the predistorter-update expands these peaks even more. It continues in this

Fig. 3. AM/AM and AM/PM curves of the class-AB PA used in the tests.

way until the predistortion signal literally “explodes”. This expansion happens very quickly; after the first step the PAPR is expanded by at least 6 dB at moderate power levels. In the second step the PAPR can increase by another 6-10 dB. Continuing in this way can result in signals with PAPR of more than 25 dB [15]. In the present paper it is experimentally illustrated for a 60W class-AB PA that the peak power of the predistortion input signal increases by more than 25 dB due to the attempt at compensating the compression. However, the expansion is stopped at 10 dB in order to avoid damaging the tested amplifier.

To illustrate the compression distortion of a PA, the amplitude/amplitude (AM/AM) and amplitude-phase (AM/PM) distortions of the tested PA are shown in Fig. 3 estimated using a 20 MHz wide orthogonal frequency division multiplex (OFDM) signal centered at 2.15 GHz. More details on the PA are given in Section III. When the amplitude of the input signal is increased, which occurs due to the DPD, the PA is further compressed. This in turn means that the DPD is updated to further increase the input signal amplitude, unless this amplitude is controlled.

The expansion is characteristic for all DPD algorithms due to the compensation of the gain compression. For a DPD with sufficient freedom to expand the signal, such as a high order polynomial or a directly trained look-up-table, the predistortion signal peak can grow to very large amplitudes if the PA is operated in deep compression without amplitude control.

C. Amplitude Controlled Predistortion

Ideally, the predistorter should turn the combined system of DPD and PA into a system that is linear at all power levels until compression has been reached, and then perform hard clipping. Using the standard ILA method there is nothing that prevents an uncontrolled expansion of the input signal.

One way of preventing this from happening is to include an explicit limit of the predistortion signal amplitude when identifying the parameters of the predistorter. In order not to lose the proven advantages of the linear least-squares

estimator we would like to continue using the parameter-linear ILA-principle but include the amplitude limitation. This restricts us to predistorter structures that are linear in the parameters, such as Volterra systems, and reductions thereof.

The problem that needs to be solved can then be expressed as

$$\min_{\eta} \|\mathbf{u} - \mathbf{H}(\mathbf{y})\eta\|_2^2 \quad (3a)$$

$$\text{s.t. } \mathbf{u}_{\text{PD}} = \mathbf{H}(\mathbf{u})\eta \quad (3b)$$

$$\|\mathbf{u}_{\text{PD}}\|_{\infty} < L \quad (3c)$$

where $\|\cdot\|_{\infty}$ denotes the infinity norm (largest absolute value in the vector) and L is the upper limit amplitude of the predistortion signal i.e., how many volts of input amplitude the PA can withstand, or the driver stages can deliver. $\mathbf{u}$, $\mathbf{y}$ and $\mathbf{H}$ are as in (1) and (2).

When the first step of the ILA is computed, it gives a large expansion of the signal. This expansion results in an extrapolation i.e., the input signal to the PA is in a higher power region than the signal used to find the predistorter parameters. To limit this extrapolation, a few different strategies can be chosen when it comes to determining L . The predistortion signal peak can be limited by the maximum signal amplitude that the driver and/or PA can withstand, a relative expansion based on the previous signal, or a relative expansion based on the original signal peak. For this paper, the minimum of a predetermined maximum input power to the PA and a relative expansion in relation to the original signal has been used. This means that the limit L in (3c) is chosen as $L = \min\{\text{peak power, relative expansion}\}$ in each step of the MS-ILA.

Essentially, (3a) is the same minimization problem as (1). The predistortion signal $\mathbf{u}_{\text{PD}}$ is computed as usual in (3b). The amplitude constraint is then stated in (3c).

The validity of the proposed approach is motivated by considering that (ideally) the samples below the specified amplitude limit L should remain unaffected by the constraint, whereas the samples above this limit should be controlled in amplitude. However, both of these requirements cannot be achieved with the same model structure as was originally used. At least a higher nonlinear order is required. The exact effects need further investigation.

For implementation, it is suitable to rewrite (3a)-(3c) as

$$\min_{\eta} \|\mathbf{u} - \mathbf{H}(\mathbf{y})\eta\|_2^2 \quad (4a)$$

$$\text{s.t. } |\mathbf{H}(\mathbf{u})\eta|^2 < \mathbf{1}L^2 \quad (4b)$$

where the absolute value $|\cdot|$ is taken over each element and $\mathbf{1}$ is a vector of appropriate size filled with ones. The inequality $<$ operates as an element-wise inequality i.e., every entry in the column vector $|\mathbf{H}(\mathbf{u})\eta|^2$ is less than the corresponding row in $\mathbf{1}L^2$.

Problems that can be solved by linear least-squares are in general desirable because they have a global optima that is easily obtained. This is clearly not possible with the problem in (4a)-(4b). However, if the problem can be shown to be convex it is known that there is a global optima that can (easily) be found [18].

Start by observing that the optimization goal is a convex function of η – it is a standard linear least-squares problem. The constraints in (4b) should now be shown to form a convex set. Consider the k :th inequality which is formed by multiplying $\mathbf{H}_k(\mathbf{u})$, being the k :th row of $\mathbf{H}(\mathbf{u})$, by η . Now, let $\eta_1, \eta_2 \in S_k$ where S_k is the set of all η that fulfills $|\mathbf{H}_k(\mathbf{u})\eta|^2 < L^2$. To show convexity of the k :th constraint, all combinations of η_1 and η_2 must be in S_k . Consider $|\mathbf{H}_k(\mathbf{u})(\alpha\eta_1 + (1 - \alpha)\eta_2)|^2 < \alpha^2|\mathbf{H}_k(\mathbf{u})\eta_1|^2 + (1 - \alpha)^2|\mathbf{H}_k(\mathbf{u})\eta_2|^2 < \alpha^2L^2 + (1 - \alpha)^2L^2 < L^2$ with $\alpha \in [0, 1]$. Thus the k :th constraint is convex. A theorem states that the intersection of two convex sets is also a convex set [18]. Hence, the problem (4a)-(4b) is convex.

To solve the convex problem in (4a)-(4b), either a general purpose convex optimization software such as CVX [23] can be used, or a tailor-made method is used. Due to the larger flexibility, the second option is chosen in this paper. The chosen method is a primal-dual interior point method. The search direction is determined by applying Newton's method to the Karush-Kuhn-Tucker (KKT) conditions [18]. The step length is obtained from backtracking line search [18].

For the Newton search, the gradients and the Hessian matrices of the objective function $f_0(\eta)$ and the constraint functions $f_k(\eta)$ are necessary. These are given in Appendix A. However, it is easier to do the required mathematics if the complex-valued signals are transformed to their real-valued counterparts. This means that the objective function (4a) is written as

$$\min_{\eta} f_0(\eta) = \min_{\eta} \|[\Re\{\mathbf{u}\}^T \Im\{\mathbf{u}\}^T]^T - [\Re\{\mathbf{H}(\mathbf{y})\eta\}^T \Im\{\mathbf{H}(\mathbf{y})\eta\}^T]^T\|_2^2 \quad (5)$$

with $\Re\{\cdot\}$ being the real part of the quantity within the brackets and $\Im\{\cdot\}$ being the imaginary part. Using a complex-to-real transform, (5) can be rewritten as

$$\min_{\eta} f_0(\eta) = \min_{\eta} \|\mathbf{u}_e - \mathbf{H}_e(\mathbf{y}_e)\eta_e\|_2^2 \quad (6)$$

with

$$\begin{aligned} \mathbf{H}_e(\mathbf{y}_e) &= \begin{pmatrix} \Re\{\mathbf{H}(\mathbf{y})\} & -\Im\{\mathbf{H}(\mathbf{y})\} \\ \Im\{\mathbf{H}(\mathbf{y})\} & \Re\{\mathbf{H}(\mathbf{y})\} \end{pmatrix} \triangleq \\ &\begin{pmatrix} \mathbf{H}_{\Re}(\mathbf{y}) & -\mathbf{H}_{\Im}(\mathbf{y}) \\ \mathbf{H}_{\Im}(\mathbf{y}) & \mathbf{H}_{\Re}(\mathbf{y}) \end{pmatrix} \\ \mathbf{y}_e &= \begin{pmatrix} \Re\{\mathbf{y}\}^T & \Im\{\mathbf{y}\}^T \end{pmatrix}^T \triangleq \begin{pmatrix} \mathbf{y}_{\Re}^T & \mathbf{y}_{\Im}^T \end{pmatrix}^T \\ \mathbf{u}_e &= \begin{pmatrix} \Re\{\mathbf{u}\}^T & \Im\{\mathbf{u}\}^T \end{pmatrix}^T \triangleq \begin{pmatrix} \mathbf{u}_{\Re}^T & \mathbf{u}_{\Im}^T \end{pmatrix}^T \\ \eta_e &= \begin{pmatrix} \Re\{\eta\}^T & \Im\{\eta\}^T \end{pmatrix}^T \triangleq \begin{pmatrix} \eta_{\Re}^T & \eta_{\Im}^T \end{pmatrix}^T \end{aligned}$$

The constraints (4b) are likewise changed into their real-valued counterparts by letting $\mathbf{H}_{\Re, k}$ denote the real-valued part of row k in the matrix $\mathbf{H}$, and $\mathbf{H}_{\Im, k}$ denote the imaginary part of row k . The constraints (4b) can then be rewritten as

$$f_k(\eta) = (\mathbf{H}_{\Re, k}\eta_{\Re})^2 + (\mathbf{H}_{\Im, k}\eta_{\Im})^2 - L^2 < 0. \quad (7)$$

It is not necessary to consider all the N samples used for finding the minimum of the objective function $f_0(\eta_e)$ when computing the constraints. Each sample corresponds to one

constraint, meaning that the number of constraints can become large if a large N is used.

Observing that the only samples that will become large after the DPD is applied are the input samples that have large amplitude. Let these samples belong to a set $\mathcal{K}$, and let the set have K samples, with $K \leq N$. It is enough to let these samples form the constraints $f_k(\eta_e)$, preferably such that $K \ll N$.

Because an iterative method (the Newton method) is used to solve the system of equations in (8), it is possible to update the samples in the set $\mathcal{K}$ after each iteration. This can further reduce the number of required constraints, thus easing the computational burden.

The problem of predistorter *blow-up* has been identified. A method based on extending the MS-ILA with a peak control was introduced and the resulting problem has been shown to belong to the class of convex optimization problems. An interior point method was proposed to solve this optimization problem.

III. MEASUREMENT PREREQUISITES

For the performance evaluation, a 20 MHz wide OFDM signal is used. It is filled with random 64-QAM modulated data on 1200 of the 2048 carriers and uses a cyclic prefix length of $1/4$. The sampling rate is 30.72 MHz and the signal is centered at 2.15 GHz. Two sets of signals are used, one for identification and one for validation, each consisting of 46 000 samples. The identification signal is always used for updating the parameters of the MS-ILA predistorter. The presented results are the results from the validation data set. Both signal sets have PAPR of approximately 11.5 dB. Any signal type could have been used but due to the recent interest in OFDM and the high PAPR associated with these signals, it is a suitable type of signal to demonstrate the effects of the peak controller with.

The measurement setup consists of a vector signal generator, combination of a R&S SMU200A and a R&S AFQ100A baseband source, an Anritsu wideband power meter, a wideband downconverter [24] and a 400 MSps analog-to-digital converter (ADC). All instruments are controlled from a PC running Matlab. A high power driver amplifier is also included in the setup to provide the necessary input signal power. The setup is shown in Fig. 4.

The device-under-test (DUT) is a single-stage, class-AB Infineon 60W RF LDMOS power transistor mounted in the manufacturer's test fixture [25]. The transistor is intended for multicarrier wideband code division multiple access (WCDMA) signals in the 2110-2170 MHz frequency range. Rated continuous wave 1 dB compression point is 68 W output power. The AM/AM- and AM/PM-curves are shown in Fig. 3. The spreading indicates that a certain amount of memory is present in the PA.

The model used for predistortion is the parallel Hammerstein model [4], [26] with nonlinear order 11 and memory depth 2. The parallel Hammerstein model has in a number of publications been shown to have low model error for a large number of PAs [27], [28]. It is also known that the inverse of

Fig. 4. Measurement setup consisting of vector signal generator (VSG), driver amplifier (DA), directional coupler, downconverter (DCNV), local oscillator (LO) for the downconverter, ADC and the DUT under test. All instruments are controlled from a PC running Matlab.

Fig. 5. Example of DPD signal (u_{DPD}), peak controlled DPD signal ($u_{\text{DPD, ctrl.}}$), the original OFDM signal (u) and the limit amplitude (L).

such a nonlinear model is well described by a similar model structure if the linear memory effects are negligible [29], [30].

Performance is evaluated by considering the PAPR, the peak input power, the EVM and the ACLR. The ACLR is defined as the maximum of the power in either of the two adjacent 20 MHz wide channels. The original signal has an ACLR of -52.5 dB. Lower ACLR can thus not be obtained with this particular signal. The EVM is defined as the sum-square-error between the input signal to the DPD (if present) and the output signal from the PA.

IV. RESULTS

The notation used in the graphs are as follows. DPD1, DPD2 and DPD5 denote the results from the MS-ILA algorithm with the number being the step number i.e., DPD2 denotes the second step in the MS-ILA. In a similar way, DPD1 ctrl. denotes the step number of the peak controlled MS-ILA proposed in this paper. Orig. are the results obtained using the original signal without DPD. All results presented in the following are measured on the 60W PA introduced in Section III. The results are for the validation data set not used to extract the predistorter parameters.

An example of the peak controlled and the standard MS-ILA signals after one step is shown in Fig. 5. There it is seen that the peak limiting keeps the peaks below the required limit whereas the standard DPD expands the peaks to large values.

In Fig. 6 the ACLR of the 20 MHz OFDM signal is shown as a function of the output root-mean-square (RMS) power.

Fig. 7 shows the EVM of the signals. In Fig. 8, the PAPR of the predistortion signals extracted at different power levels are shown. Similarly, Fig. 9 shows the peak input power as function of RMS output power.

ACLR is the main performance measure for the linearity of the PA. At power levels below 36.5 dBm, there is no ACLR performance difference between the standard MS-ILA and the controlled MS-ILA. This is expected because the expansion of the peaks is very limited, as seen in Figs. 8 and 9. Hence, the peak control is not active i.e., the constraints in (3c) are not affecting the solution to the ILA-problem in (3a). This is the reason why the performance is the same. For EVM, the performance is similar at these lower power levels.

At medium power, 36.5–38 dBm, the proposed peak control method shows slightly inferior performance compared to the standard MS-ILA. This is explained by the fact that the controlled MS-ILA should give somewhat worse results for the same model structure due to the peak limiting - the optimal unconstrained solution can choose any parameter combination compared to the constrained solution where the parameters must result in a solution where the amplitude of the predistortion signal is reduced. The EVM is slightly worse when using the peak controller but the degradation is still acceptable for most wireless standards.

In order to protect the PA from being destroyed due to high signal peaks, the input peak power was limited to 42.5 dBm. This peak power level roughly corresponds to a gain compression of 10 dB i.e., 5.7 dB gain compared to the small-signal gain of 15.7 dB. The first step of the standard MS-ILA is operable up to 37.8 dBm output power, the second step to 37.5 dBm, third step to 37.1 dBm, fourth and fifth step to 37 dBm. Beyond the stated power levels, the input peak powers increase in such a way that the signal cannot be transmitted without damaging the PA. This is not shown in Figs. 6–10. This occurs because the DPD attempts to compensate the compression by increasing expansion.

However, the controlled MS-ILA can still be used at these higher power levels. In terms of ACLR, EVM, PAPR and peak input power, the controlled MS-ILA appears to converge. The first step shows large variations in performance, but this is expected due to the extrapolation associated with the predistortion. The second step improves both ACLR and EVM, indicating that the changes in signal characteristics are properly handled. The third and fourth step do not improve the performance significantly and we only show the fifth step when the DPD has settled to its' final value. Note that at the higher power levels, close to 39 dBm, the second step of the controlled MS-ILA significantly improves both ACLR and EVM. Nevertheless, the ACLR is above the limit of -40 dB when this output power is used.

The peak input power after one step of the uncontrolled MS-ILA is shown in Fig. 10 as function of input RMS power to the PA. Note that the RMS input power is considerably increased due to the predistorter expansion. A second step of the MS-ILA is not possible with such peak power levels for this device.

We see from Figs. 8 and 9 that the PAPR and the peak input power are kept much lower using the controlled MS-

Fig. 6. The ACLR of the signal when passing through the class-AB PA for steps 1, 2 and 5 of the original MS-ILA (DPD1, DPD2 and DPD5) and the corresponding steps of the peak controlled MS-ILA (DPD1 ctrl., DPD2 ctrl. and DPD5 ctrl.). The performance when using the original signal is shown for reference. At higher power levels no results are presented for the standard MS-ILA because the large peak powers make measurements impossible. However, the controlled MS-ILA produces results that appear to converge.

Fig. 7. The EVM is shown in the same way as the ACLR in Fig. 6.

ILA method. This is of benefit for the whole transmitter chain including baseband signal processing and DACs, because the necessary resolution in the signal generation can be achieved using fewer bits. The reduced input peak powers also eases the requirements on the driver stages and stresses the power transistors less and should reduce the risk of early transistor failure.

However, the main advantage is that the peak control stabilizes the predistorter at higher power levels. In other words, the peak control prevents the “blow-up” normally associated with predistortion of compressive PAs.

Parallel Hammerstein models with other nonlinear orders and memory depths have also been tested but these results are not presented here. They all showed the same general behavior both with the standard MS-ILA and the controlled MS-ILA.

Fig. 8. The PAPR of the input signals for the MS-ILA, the peak controlled MS-ILA and the original signal. For the original MS-ILA the PAPR increases with power and with the iteration number. The controlled MS-ILA limits the PAPR to the minimum of 3 dB expansion relative to the previous peak power, and 42.5 dBm.

Fig. 9. Peak powers of the predistortion signals i.e., PA input signals, for the same steps as those used in Fig. 6. The original signal peak power is shown for reference.

V. CONCLUSIONS

Uncontrolled expansion of the input signal to an RF PA generated by using a predistorter is found to be a problem. Typical increase in PAPR for a class-AB PA, using a single step of the ILA predistorter with a parallel Hammerstein model results in uncontrolled increases of the signal PAPR if the signal peaks are in the compression region. Using further steps of the MS-ILA further increases the PAPR in each step.

A method that allows the user to control the peak output power of the predistortion signal while benefiting from the MS-ILA is proposed. It is illustrated how the proposed solution can be used with the MS-ILA to update the predistorter parameters to account for changing conditions while reducing the problems of “*predistorter blow-up*” i.e., uncontrolled peak power increase. The formulated optimization problem is shown

Fig. 10. Peak powers as in Fig. 9 but as function of the input RMS power. The peak power of the first step of the MS-ILA is shown to illustrate the problem of peak (and RMS) power expansion in standard DPD methods.

to be convex and a primal-dual interior point method is suggested to solve it.

Measurements with OFDM-signals on a class-AB PA show that the linearization performance is significantly improved in the compression region using the proposed scheme. The output power could be increased by approximately 1 dB while fulfilling the linearity requirements of less than -40 dB ACLR. At the same time the PAPR and the peak input power of the predistortion signal is kept considerably lower, resulting in reduced requirements on signal generation (DAC resolution, mixer and driver amplifier distortions) and the number of bits in the baseband signal processing, in addition to reduced peak power requirements in the driver and PA stages.

The largest advantage is that of being able to explicitly control the peaks of the predistortion signal. This reduces the problem of the “*predistorter blow-up*” encountered when operating the PA in compression.

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APPENDIX

GRADIENTS AND HESSIAN MATRICES FOR THE PRIMAL-DUAL ALGORITHM

A solution to the convex optimization problem is obtained when the KKT-conditions are fulfilled. By solving for the modified KKT-conditions in [18], the primal-dual interior point method is obtained. The modified KKT-system of equations to be solved for the Newton step direction $[\Delta\eta_e^T \Delta\lambda^T]^T$ is shown in (8).

$$\mathbf{G}\Delta = -\mathbf{r} \quad (8)$$

with

$$\mathbf{G} = \begin{pmatrix} \nabla^2 f_0(\eta_e) + \sum_{k=1}^K \lambda_k \nabla^2 f_k(\eta_e) & D\mathbf{f}(\eta_e)^T \\ -\text{diag}(\lambda) D\mathbf{f}(\eta_e) & -\text{diag}(\mathbf{f}(\eta_e)) \end{pmatrix}, \quad (9a)$$

$$\Delta = \begin{pmatrix} \Delta \eta_e \\ \Delta \lambda \end{pmatrix} \quad (9b)$$

and

$$\mathbf{r} = \begin{pmatrix} r_{\text{dual}} \\ r_{\text{cent}} \end{pmatrix} = \begin{pmatrix} \nabla f_0(\eta_e) + D\mathbf{f}(\eta_e)^T \lambda \\ -\text{diag}(\lambda) \mathbf{f}(\eta_e) - (1/t) \mathbf{1} \end{pmatrix} \quad (9c)$$

In (8), $r_{\text{dual}} = \nabla f_0(\eta_e) + D\mathbf{f}(\eta_e)^T \lambda$ and $r_{\text{cent}} = -\text{diag}(\lambda) \mathbf{f}(\eta_e) - (1/t) \mathbf{1}$. $t > 0$ is a parameter, see [18] for details.

In (8), λ are the Lagrange multipliers for the constraints, $[(\Delta \eta_e)^T (\Delta \lambda)^T]^T$ is the primal-dual search direction, r_{dual} is the dual residual, r_{cent} is the centrality residual [18] and K is the number of constraints. $D\mathbf{f}(\eta_e)$ is given by

$$D\mathbf{f}(\eta_e) = \begin{pmatrix} \nabla f_1(\eta_e) \\ \nabla f_2(\eta_e) \\ \vdots \\ \nabla f_K(\eta_e) \end{pmatrix}, \quad (10)$$

$$\mathbf{f}(\eta_e) = \begin{pmatrix} f_1(\eta_e) \\ f_2(\eta_e) \\ \vdots \\ f_K(\eta_e) \end{pmatrix} \quad (11)$$

and $\text{diag}(\lambda)$ is a diagonal matrix with the elements of λ on the diagonal.

In (12a) and (12b) the expression for the gradient, respectively the Hessian, of the objective function, are given. Correspondingly, (13a) and (13b) gives the gradients and the Hessians of the constraint functions.

$$\nabla f_0(\eta_e) = 2(\mathbf{H}_e(\mathbf{y}_e)^T \mathbf{H}_e(\mathbf{y}_e) \eta_e - \mathbf{H}_e(\mathbf{y}_e)^T \mathbf{u}) \quad (12a)$$

$$\nabla^2 f_0(\eta_e) = 2\mathbf{H}_e(\mathbf{y}_e)^T \mathbf{H}_e(\mathbf{y}_e) \quad (12b)$$

$$\nabla f_k(\eta_e) = 2(\mathbf{H}_{\mathcal{R},k}(\mathbf{u}_e) \eta_{\mathcal{R}} - \mathbf{H}_{\mathcal{I},k}(\mathbf{u}_e) \eta_{\mathcal{I}}) \cdot \begin{pmatrix} \mathbf{H}_{\mathcal{R},k}(\mathbf{u}_e)^T \\ -\mathbf{H}_{\mathcal{I},k}(\mathbf{u}_e)^T \end{pmatrix} \quad (13a)$$

$$\nabla^2 f_k(\eta_e) = 2 \left(\mathbf{H}_{\mathcal{R},k}^T \begin{bmatrix} \mathbf{H}_{\mathcal{R},k}^T \\ -\mathbf{H}_{\mathcal{I},k}^T \end{bmatrix}^T \right) + 2 \left(\mathbf{H}_{\mathcal{I},k}^T \begin{bmatrix} \mathbf{H}_{\mathcal{R},k}^T \\ \mathbf{H}_{\mathcal{I},k}^T \end{bmatrix}^T \right). \quad (13b)$$

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