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# An Efficient Method to Study the Trade-off between Power Amplifier Efficiency and Digital Predistortion Complexity

Siqi Wang, Morgan Roger, Julien Sarrazin, *Member, IEEE*, and Caroline Lelandais-Perrault

**Abstract**—This paper proposes a method to study the trade-off between the power amplifier (PA) power efficiency and the corresponding digital predistortion (DPD) model complexity needed for its linearization. The linearization performance estimated with the adjacent channel power ratio (ACPR) is treated as a control variable. In order to study at different PA operating points (OP), an algorithm is proposed to trace approximate Pareto fronts of the ACPR versus the DPD model number of coefficients. Crest factor reduction is applied when the backoff of the OP is less than the peak-to-average power ratio (PAPR) of the Long Term Evolution (LTE) signal. Experimental results on a PA with an LTE signal give interesting insights on the relation between DPD complexity and PA power efficiency.

**Index Terms**—Crest factor reduction, digital predistortion, nonlinear distortion, power amplifiers, power efficiency

## I. INTRODUCTION

DIGITAL predistortion (DPD) is a common method to compensate for nonlinearities of radio frequency (RF) power amplifiers (PA) allowing it to work in high power efficiency zone near saturation [1]. This is typically advantageous when the PA output power is high enough so that the DPD power consumption is negligible.

However, in modern telecommunication systems, the PA output power requirements may vary. In cases where the DPD power consumption might become non-negligible, one can look for the best trade-off from the PA operating point (OP) of view. Since the DPD is applied to save power by increasing the PA efficiency, the power consumed by the DPD needs to be assessed with respect to the saved power [2]. Also, at the first order, the DPD power consumption is related to the number of its model coefficients [3].

DPD and crest factor reduction (CFR) techniques control the PA power efficiency [4] by allowing to adjust the PA OP. Different OPs lead to different PA characteristics and thus the DPD model structure should be correspondingly adapted so that the linearization performance remains the same.

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In this paper, the final goal is to make a study on the trade-off between PA power efficiency and the necessary DPD complexity to achieve a given adjacent channel power ratio (ACPR) requirement. To do that, we propose an algorithm to estimate the minimum number of DPD coefficients at a chosen PA OP for different ACPR requirements. Then we apply this algorithm on data acquired from a PA at different OPs and visualize the relation between PA power efficiency and DPD complexity.

This paper is organized as follows. Section II presents the DPD model. An algorithm is introduced to plot approximate Pareto fronts for the DPD complexity versus its linearization performance in Section III. In section IV, the PA efficiency is measured and the DPD complexity is estimated according to the experimental results. Finally, section V gives a conclusion.

## II. CREST FACTOR REDUCTION AND DIGITAL PREDISTORTION

The system architecture is illustrated in Fig 1, where, the output signals of the CFR and the DPD are denoted by  $u_c(n)$  and  $x(n)$  respectively. In cases where the OP has an input back-off less than the input signal peak-to-average power ratio (PAPR), the clip-and-filter method [5] is used in this paper as CFR technique with the number of iterations set at 10 as suggested in [4].

Regarding DPD identification, we use the indirect learning architecture to estimate PA post-inverse model coefficients as in Fig 1. Numerous DPD models have been proposed based on Volterra Series, e.g. generalized memory polynomial (GMP) [1], dynamic-deviation-reduction (DDR) model [6] and decomposed vector rotation-based behavioral model (DVR) [7], etc. We use the GMP in this paper since it exhibits good trade-off between modeling accuracy and model complexity [3]. The post-inverse output  $z_p(n)$  modeled with the GMP can be written as:

$$z_p(n) = \sum_{k=0}^{\mathcal{K}_a-1} \sum_{l=0}^{\mathcal{L}_a-1} a_{kl} z(n-l) |z(n-l)|^k + \sum_{k=1}^{\mathcal{K}_b} \sum_{l=0}^{\mathcal{L}_b-1} \sum_{m=1}^{\mathcal{M}_b} b_{klm} z(n-l) |z(n-l-m)|^k + \sum_{k=1}^{\mathcal{K}_c} \sum_{l=0}^{\mathcal{L}_c-1} \sum_{m=1}^{\mathcal{M}_c} c_{klm} z(n-l) |z(n-l+m)|^k \quad (1)$$

where the input signal is  $z(n)$  which is the PA output  $y(n)$  divided by  $g$ , the nominal gain of PA,  $k$  is the index for

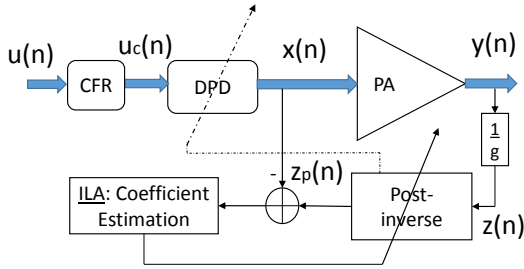


Fig. 1. Indirect learning architecture (ILA)

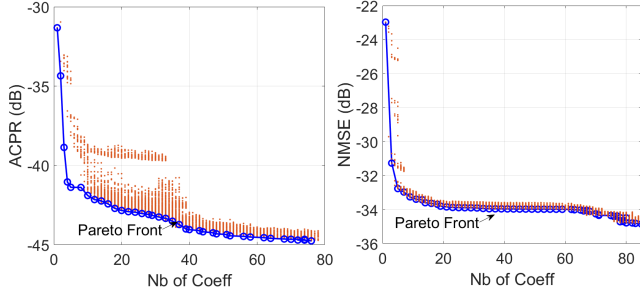


Fig. 2. The proposed algorithm traces out an approximate Pareto Front composed of optimal models

nonlinearity, and  $l, m$  are the indices for memory,  $\mathcal{K}_a, \mathcal{K}_b, \mathcal{K}_c$  are the highest orders of nonlinearity.  $\mathcal{L}_a, \mathcal{L}_b, \mathcal{L}_c$  are the highest memory depths.  $\mathcal{M}_b, \mathcal{M}_c$  denote the longest lagging and leading delay tap length, respectively.  $a_{kl}, b_{klm}, c_{klm}$  are the complex coefficients of the signal and envelope, the signal and lagging envelope, and the signal and leading envelope, respectively. These coefficients can be estimated using least squares (LS) as in [8] by solving:

$$[\mathbf{Z}^H \mathbf{Z}] \hat{\mathbf{c}} = \mathbf{Z}^H \mathbf{x} \quad (2)$$

which minimizes the cost function

$$C = \sum_{n=1}^N |z_p(n) - x(n)|^2. \quad (3)$$

where  $\mathbf{x}$  is the PA input,  $\mathbf{Z}$  is the  $N \times R$  matrix containing basis functions of  $\mathbf{z}$ ,  $\mathbf{c}$  is a  $R \times 1$  vector containing  $a_{kl}, b_{klm}, c_{klm}$ ,  $R$  is the total number of coefficients.

### III. ALGORITHM FOR OPTIMAL SOLUTIONS

According to (1), we can see that, by varying values of  $(\mathcal{K}_a, \mathcal{L}_a, \dots, \mathcal{M}_c)$ , DPD models with the same number of coefficients may correspond to different structures thus different linearization performance.

The linearization performance is evaluated here with the ACPR of the post-inverse output  $z_p(n)$ . It could also be evaluated with the normalized mean square error (NMSE) or error vector magnitude (EVM) between  $z_p(n)$  and  $x(n)$ . In order to know the necessary DPD complexity, we need to find out for each number of coefficients the corresponding DPD model with the best ACPR values.

In [8], an algorithm based on the Hill-Climbing heuristic has been proposed to determine an optimal DPD structure. It mainly addresses solving an optimization problem within a short time.

### Algorithm 1: Algorithm to trace Pareto front

```

Initialize  $d = d_{init}, q=1$ ;
Add  $t_{0(1)}$  to the Pareto front and set it as starting point;
while  $R_{0(q)} \leq R_{limit}$  &  $d \leq R_{limit}$  do
    Find the best  $t_{s(q)}$  in  $S_{(q)}(d)$ ;
    if  $A(t_{s(q)}) < A(t_{0(q)})$  then
        Add  $t_{s(q)}$  into the Pareto front;
         $t_{0(q+1)} = t_{s(q)}$ ;
         $d = d_{init}, q = q + 1$ ;
    else
         $d = d + 1$ ;
    end
end

```

Algorithm 1 summarizes the modified version proposed in this paper and detailed below. It allows users to obtain all optimal solutions with different number of coefficients and to choose the most appropriate model structure according to their customized criterion. It gives out all models with the lowest ACPR/NMSE values as the blue curve in Fig 2 without doing an exhaustive search. The red points are the models tested in the algorithm. The blue circles are Pareto-optimal points such that there is no point who outperforms them on both ACPR and number of coefficients. The set of Pareto-optimal solutions is called Pareto front [9].

We define a neighbor  $t_j$  of the model  $t_i$  as

- 1) an 8-tuple  $(\mathcal{K}_{a,i} + \delta_1, \mathcal{L}_{a,i} + \delta_2, \dots, \mathcal{M}_{c,i} + \delta_8)$ , where  $\delta_{1,\dots,8} \in [0, \pm 1]$  and  $\delta_{1,\dots,8}$  are not 0 at the same time.
- 2)  $|R_i - R_j| < d$  where  $d$  is a constraint on the number of coefficients.

The subspace of neighbors is denoted by  $S(d)$ .

The first starting point  $t_0$  is the simplest model. The constraint  $d$  is initialized at  $d_{init} = 2$  and it increases when there is no better element in  $S(d)$ . If a better neighbor  $t_s$  is then found,  $d$  is reset to its initial value. We set a constraint  $R_{limit}$  on the total number of coefficients. 6658 and 6563 models were tested to plot the Pareto front for respectively ACPR and NMSE in Fig. 2. Using the exhaustive search, if each parameter is limited to 10, there will be more than  $10^8$  models to test. The study on the relation between PA efficiency and its DPD complexity needs to explore a large amount of OPs. Using the proposed algorithm can save enormous time.

### IV. EXPERIMENTAL RESULTS

With the algorithm proposed in Section III, we can quickly obtain the DPD models with best ACPR or NMSE values at different PA OPs. The PA under test is a HMC409LP4E PA fabricated by Analog Devices. Its nominal gain at 3.5 GHz is 31 dB and the saturated output power is 32.5 dBm. The supply voltage is 5 V. We generate the modulated signal with a carrier frequency of 3.5 GHz in the PC Workstation and feed it to the PA through an Arbitrary Waveform Generator (AWG) with 10 GHz sampling frequency. The input and output baseband signals are synchronized after down-sampling to 120 MHz to be used by the identification algorithm.

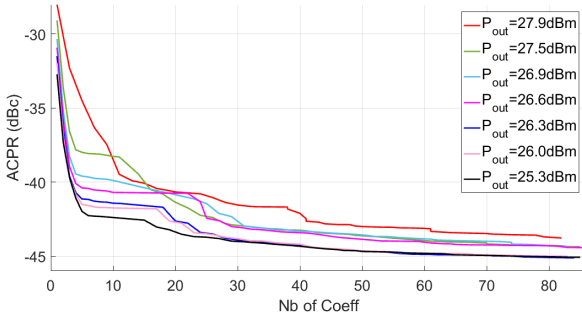


Fig. 3. Pareto fronts of the ACPR versus the number of DPD coefficients for different PA OPs

TABLE I  
IMPACT OF THE PA OP ON PA EFFICIENCY AND NECESSARY NUMBER OF DPD COEFFICIENTS FOR DIFFERENT ACPR REQUIREMENTS

$P_{in}$ (dBm)	-1.0	-0.1	0.6	1.1	1.2	2.6	3.6	
$I_{supply}$ (A)	0.73	0.77	0.79	0.81	0.83	0.87	0.92	
$P_{out}$ (dBm)	25.3	26.0	26.3	26.6	26.9	27.5	27.9	
PAE (%)	9.3	10.4	10.8	11.4	11.9	12.8	13.4	
R	A:-37	1.9	2.1	2.2	2.4	2.6	3.4	8.2
	A:-39	2.7	2.8	2.9	3.1	3.7	12.8	10.5
	A:-41	3.8	4.2	4.7	23.1	21.6	18.9	25.8
	A:-42	5.2	17.5	18.8	25.0	27.0	23.0	39.2
	A:-43	16.8	21.8	22.9	29.2	31.8	31.8	49.5
	A:-43.5	20.9	25.6	26.5	42.4	47.8	46.5	70.7
	A:-43.7	23.8	27.4	27.8	45.7	54.7	52.6	79.1
	A:-44	29.6	31.3	34.5	57.5	70.3	61.7	-
	A:-44.3	38.9	40.4	41.2	80.3	79.7	82.0	-

A: ACPR requirements in dBc.  
R: Number of DPD coefficients.

TABLE II  
IMPACT OF THE PA OP ON PA EFFICIENCY AND NECESSARY NUMBER OF DPD COEFFICIENTS FOR DIFFERENT NMSE REQUIREMENTS

PAE (%)	9.3	10.4	10.8	11.4	11.9	12.8	13.4	
R	NE:-30	2.7	2.7	2.7	2.8	2.9	5.3	20.7
	NE:-32	8.3	5.8	4.5	4.0	5.9	10.9	-
	NE:-33	15.3	17.3	15.3	7.2	62.4	21.2	-
	NE:-34	24.2	31.6	40.5	62.5	-	82.0	-

NE: NMSE level in dB.  
R: Number of DPD coefficients.

A 20 MHz LTE signal with 614400 samples is used as stimulus and 25000 samples are used in iterative DPD identifications. Its PAPR at  $10^{-4}$  probability level is 8 dB.

We use as a measure of efficiency the PA power-added efficiency (PAE). For different PA OPs, e.g. the average output power varying between 25.3 dBm and 27.9 dBm, we apply the algorithm proposed in Section III to obtain the Pareto fronts as illustrated in Fig 3 and Fig 4 for ACPR and NMSE respectively. The CFR technique described in Section II is applied to keep signal samples out of the PA saturation zone.

In order to study the relation between the PAE and the DPD complexity, we treat the ACPR or NMSE value as a control variable. Thus we make a linear interpolation to estimate the number of coefficients corresponding to a given ACPR or NMSE and we keep decimals to preserve the accuracy. Table I gives the PA efficiency and the necessary number of DPD coefficients for different ACPR requirements at different PA OPs.

The DPD complexity versus the PA efficiency is then plotted

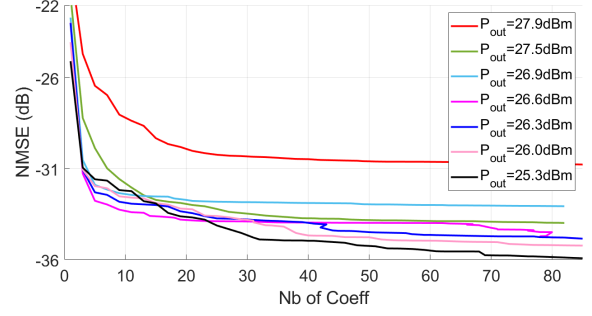


Fig. 4. Pareto fronts of the NMSE versus the number of DPD coefficients for different PA OPs

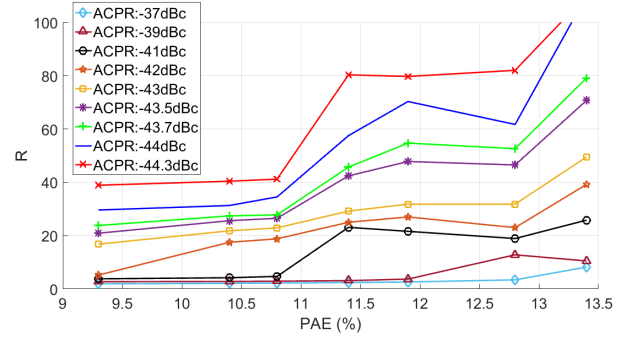


Fig. 5. DPD complexity vs PA efficiency

in Fig 5. For the tested PA, the higher the ACPR requirement is, the larger dynamic of the DPD complexity is versus the PA efficiency. This means that the DPD complexity limits more on the PAE when the ACPR requirement becomes strict.

Thanks to this method, the system designers will be able to optimize their choices. For instance, with a high ACPR requirement, it may not be worth to increase the PAE of the tested PA up to 13.4% considering the added DPD complexity.

For loose ACPR requirements, the PAE does not influence much the necessary DPD complexity. On the other hand, for strict ACPR requirements, the DPD complexity and consequently the DPD power consumption increases rapidly with the PAE, meaning the optimal OP w.r.t. the overall power consumption needs to be further studied.

The results for the NMSE as the control variable are given in Table II. We can see that the NMSE is strictly kept lower than -30 dB when the DPD has more than 20 coefficients.

## V. CONCLUSION

In this paper, an modified algorithm is proposed to trace approximate Pareto fronts for studying the trade-off between DPD model complexity and its linearization performance. It then helps to study the influence of the PA OP on the PA power efficiency and the necessary number of DPD coefficients for different ACPR or NMSE requirements with a reduced number of tests compared to the exhaustive search. Measurements with a 20 MHz LTE stimulus show that the trade-off between the power saved from the PA dissipation and the DPD power consumption heavily depends on the ACPR requirement: the more stringent it is, the more room there is to optimize the trade-off.

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