Study on the Trade-off between PA Power Efficiency and DPD Complexity

Siqi Wang, Morgan Roger, Caroline Lelandais-Perrault, Julien Sarrazin

To cite this version:

Siqi Wang, Morgan Roger, Caroline Lelandais-Perrault, Julien Sarrazin. Study on the Trade-off between PA Power Efficiency and DPD Complexity. 2019. hal-02054967v1

HAL Id: hal-02054967

https://centralesupelec.hal.science/hal-02054967v1

Preprint submitted on 2 Mar 2019 (v1), last revised 6 Dec 2019 (v2)

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Study on the Trade-off between PA Power Efficiency and DPD Complexity

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

***Abstract*—This paper investigates 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 is estimated with the adjacent channel power ratio (ACPR). A hill-climbing algorithm is proposed to trace approximate Pareto fronts of the ACPR versus the DPD model number of coefficients at different PA operating points (OP). Crest factor reduction is applied when the backoff of the OP is less than the peak-to-average power ratio (PAPR) of the LTE signal. Experimental results on a PA with a Long Term Evolution (LTE) signal give interesting insights on the relation between DPD complexity and PA power efficiency for a given ACPR requirement. Finally we propose a criterion for the trade-off between the PA efficiency and the DPD complexity in function of the ACPR requirement.**

***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). The basic idea of DPD is to apply a nonlinear model with the inverse characteristics of the PA [1] on its input signal, allowing the PA to work in high power efficiency zone near saturation. This is typically used when the PA output power is high enough that the DPD power consumption is negligible.

However, in modern telecommunication systems, the PA output power requirements may vary. In cases when 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 the power by increasing the PA efficiency, the power consumed by the DPD needs to be considered whether it is more than the saved power [2].

The DPD power consumption depends on its model complexity. Different operating points lead to different PA characteristics and thus the DPD model should be correspondingly adapted so that the linearization performance remains the same. Moreover the input signal peak-to-average power ratio (PAPR) imposes a constraint on the OP. If the backoff of the OP is less than the input signal PAPR, some samples of the signal fall into the PA saturation zone, which will degrade the linearization performance. Crest factor reduction (CFR) techniques [3] are used to address this problem.

S. Wang, M. Roger, C. Lelandais-Perrault are with GeePs — Group of electrical engineering - Paris, CNRS, CentraleSupélec, Univ. Paris-Sud, Université Paris-Saclay, Sorbonne Université, 3 & 11 rue Joliot-Curie, Plateau de Moulon 91192 Gif-sur-Yvette CEDEX, France (e-mail of authors: first-name.surname@centralesupelec.fr).

J. Sarrazin is with the Sorbonne Université, Laboratory of Electronics and Electromagnetism, L2E, F-75005 Paris, France (e-mail: julien.sarrazin@upmc.fr).

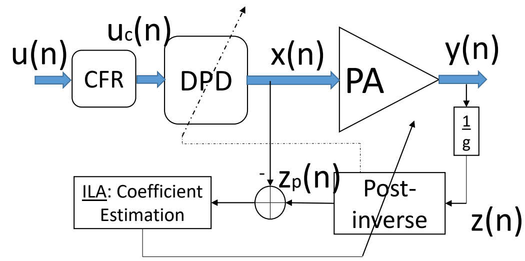

Fig. 1. Indirect learning architecture

In [4], an algorithm has been developed for an optimal DPD model with respect to the trade-off between modeling accuracy and model complexity. This paper proposes a modification on this algorithm to trace approximate Pareto fronts so that we can estimate the necessary minimum number of DPD coefficients to achieve some certain ACPR requirements. Then we make a study on the trade-off between PA power efficiency and DPD complexity taking consideration of ACPR requirements according to the experimental measurement results.

This paper is organized as follows. Section II presents the CFR and DPD models. An algorithm to plot approximate Pareto fronts for the DPD complexity versus its linearization performance is introduced in Section III. In section IV, The PA efficiency is measured and the DPD complexity are 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. In cases when the back-off of the OP is less than the input signal PAPR, the signal needs to be clipped to avoid the PA saturation zone:

$$u_c^{raw}(n) = \begin{cases} u(n)\frac{P}{|u(n)|} & \text{if } |u(n)| \geq P, \\ u(n) & \text{otherwise.} \end{cases} \quad (1)$$

where P is threshold. However this hard clipping brings distortion in all bands. In order to remove out-of-band frequency components, a filter that has the same bandwidth B as $u(n)$ is applied on the correction signal $c_r^{raw}(n) = u(n) - u_c^{raw}(n)$:

$$\mathcal{F}\{c_r\} = \begin{cases} \mathcal{F}\{c_r^{raw}\}(\omega) & \text{if } \omega \in [-\frac{B}{2}, \frac{B}{2}], \\ 0 & \text{otherwise,} \end{cases} \quad (2)$$

where $\mathcal{F}\{\cdot\}$ represents Fourier transform. The clipped signal is then $u_c(n) = u(n) - c_r(n)$. We repeat this approach iteratively to reduce the new peaks generated by filtering. In this paper, the number of iterations is set at 10.

Regarding DPD identification, we use indirect learning architecture to first estimate a post-inverse of the PA and then use it as a DPD as in Fig 1. The output of the post-inverse block $z_p(n)$ modeled with the generalized memory polynomial (GMP) can be written as [1]:

$$z_p(n) = \sum_{l=0}^{\mathcal{L}_a-1} z(n-l)A_l + \sum_{l=0}^{\mathcal{L}_b-1} z(n-l)B_l + \sum_{l=0}^{\mathcal{L}_c-1} z(n-l)C_l \tag{3}$$

where $A_l = \sum_{k=0}^{\mathcal{K}_a-1} a_{kl}|z(n-l)|^k$ is the diagonal branch gain, $B_l = \sum_{k=1}^{\mathcal{K}_b}\sum_{m=1}^{\mathcal{M}_b} b_{klm}|z(n-l-m)|^k$ and $C_l = \sum_{k=1}^{\mathcal{K}_c}\sum_{m=1}^{\mathcal{M}_c} c_{klm}|z(n-l+m)|^k$ are gains with lagging and leading delay respectively, a_{kl}, b_{klm}, c_{klm} are coefficients, z is the output y normalized by the PA gain g.

These coefficients can be estimated using least square (LS) method as in [4] by solving:

$$[\mathbf{Z}^H\mathbf{Z}]\hat{\boldsymbol{c}} = \mathbf{Z}^H\boldsymbol{x} \tag{4}$$

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

III. ACPR vs DPD Complexity

We aim to optimize two objectives: the modeling accuracy and the model complexity. The modeling accuracy is evaluated here with the adjacent channel power ratio (ACPR) of the post-inverse output $z_p(n)$ as the search criterion:

$$\mathrm{Y} = 10\log_{10}\left[\frac{\sum_{\omega\in L}|\mathcal{F}\{z_p\}(\omega)|^2 + \sum_{\omega\in U}|\mathcal{F}\{z_p\}(\omega)|^2}{2\times\sum_{\omega\in M}|\mathcal{F}\{z_p\}(\omega)|^2}\right] \tag{5}$$

where M represents the pass band of the signal, and L and U represent the lower and upper adjacent channel respectively. And the model complexity is represented by the number of DPD coefficients R. In this multi-object optimization problem, a Pareto-optimal solution t^* is such that there exists no t_i that $Y(t_i) < Y(t^*)$ or $R(t_i) < R(t^*)$. The set of Pareto-optimal solutions is called Pareto front [5].

In [4], an algorithm based on Hill-Climbing heuristic has been proposed to determine an optimal DPD structure respecting the trade-off between the modeling accuracy and the model complexity. Here we propose a modified version to trace an approximate Pareto front as in Fig 2. The red points are the models tested in the algorithm.

We define a neighbor of the model t_i as t_j:

1) an 8-tuple ($\mathcal{K}_{a,i}+\delta_1$, $\mathcal{L}_{a,i}+\delta_2$, ..., $\mathcal{M}_{c,i}+\delta_8$), where $\delta_{1,\ldots,8} \in [0, \pm 1]$ and $\delta_{1,\ldots,8}$ 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 as it is surely on the Pareto Front. The value of 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} to stop when the tested models have too many coefficients. The procedure is described as Algorithm 1.

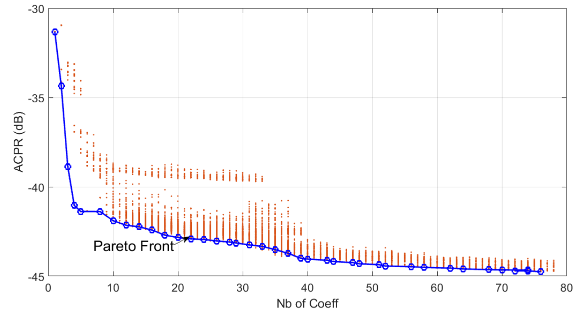

Fig. 2. ACPR vs Number of DPD coefficients

Algorithm 1: Algorithm to trace Pareto front

```
Initialize d = d_init, q=1;
Take t_0(1) into Pareto set and set as starting point;
while R_0(q) ⩽ R_limit & d ⩽ R_limit do
    Find the best t_s(q) in S_(q)(d);
    if Y(t_s(q)) < Y(t_0(q)) then
        Take t_s(q) into Pareto set;
        t_0(q+1) = t_s(q);
        d = d_init, q = q + 1;
    else
        d = d + 1;
    end
end
```

IV. Experiment Results

The test bench is illustrated in Fig 3. The PA under test is a HMC409LP4E PA fabricated by Analog Devices. Its nominal gain at 3.5 GHz frequency is 31 dB and the saturated output power is 32.5 dBm. The supply voltage is 5 V. Because of the power limit of the Arbitrary Waveform Generator (AWG), we use a TA020-060-30-27 PA fabricated by Transcom as the driver in front of the PA. Its nominal gain is 30 dB and the output power at 1dB gain compression is 27 dBm.

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 AWG with 10 GHz sampling frequency. The input and output baseband signals are synchronized in time after down-sampling to 120 MHz to be used by the identification algorithm.

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.

In this paper we use as a measure of efficiency the PA power-added efficiency (PAE) defined as

$$\eta = \frac{P_{out} - P_{in}}{P_{supply}}, \tag{6}$$

where P_{in} and P_{out} are the PA input and output powers respectively, P_{supply} is the power provided by the supply.

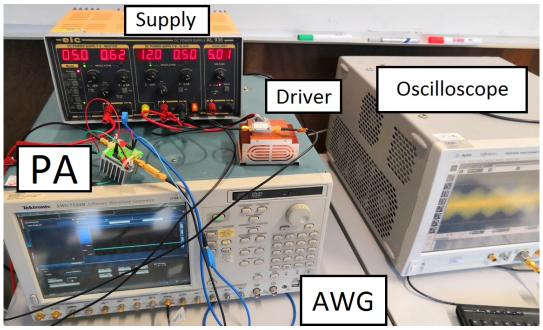

Fig. 3. Test bench

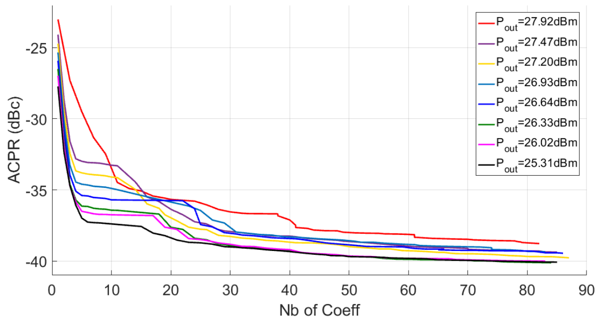

Fig. 4. Pareto Fronts of the ACPR versus the number of DPD coefficients for several PA operating points

For different PA operating points with 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 illustrated in Fig 4. The CFR technique is applied to keep the signal samples out of the PA saturation zone.

Since the number of DPD coefficients is an integer, we may not have a real model that reaches the exact same ACPR as the given ACPR requirement. Simply taking the number of coefficients of a model that has a lower ACPR value than the requirement will reduce the estimation precision. Thus we estimate the minimum number of coefficients using linear interpolation.

Table I gives the PA efficiency and necessary number of DPD coefficients for different ACPR requirements at different PA operating points. The DPD complexity versus the PA efficiency is then plotted in Fig 5.

For all cases of ACPR requirements, improving the PA efficiency demands a DPD with higher complexity. The higher the ACPR requirement is, the larger the variation dynamic of the DPD complexity is versus the PA efficiency. For loose ACPR requirements, the PA operating point does not influence much the needed DPD complexity. On the other hand, for strict ACPR requirements, the DPD complexity increases rapidly with the PA output power. This means that the importance of the DPD complexity increases with the ACPR requirement.

V. Conclusion

In this paper, a modified algorithm is proposed to trace approximate Pareto fronts for the trade-off between DPD model complexity and its linearization performance. We then study the influence of the PA operating point on the PA power efficiency and the necessary number of DPD coefficients for different ACPR requirements. 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.

TABLE I
Impact of the PA operating point 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:-32	1.9	2.1	2.2	2.4	2.6	3.4	8.2
	A:-34	2.7	2.8	2.9	3.1	3.7	12.8	10.5
	A:-36	3.8	4.2	4.7	23.1	21.6	18.9	25.8
	A:-37	5.2	17.5	18.8	25	27	23	39.2
	A:-38	16.8	21.8	22.9	29.2	31.8	31.8	49.5
	A:-38.5	20.9	25.6	26.5	42.4	47.8	46.5	70.7
	A:-38.7	23.8	27.4	27.8	45.7	54.7	52.6	79.1
	A:-39	29.6	31.3	34.5	57.5	70.3	61.7	-
	A:-39.3	38.9	40.4	41.2	80.3	79.7	82.0	-

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

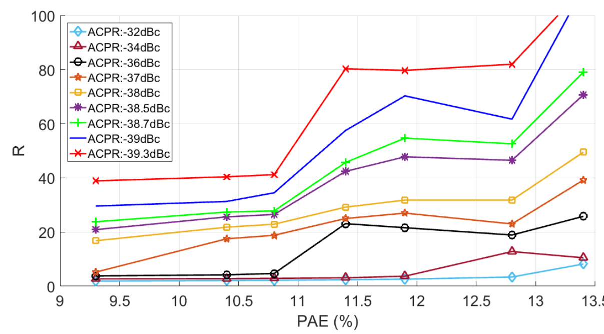

Fig. 5. DPD complexity vs PA efficiency

References

[1] D. Morgan, Z. Ma, J. Kim, M. Zierdt, and J. Pastalan, "A generalized memory polynomial model for digital predistortion of rf power amplifiers," *IEEE Trans. Signal Process.*, vol. 54, no. 10, pp. 3852–3860, Oct. 2006.

[2] S. Boumard, M. Lasanen, O. Apilo, A. Hekkala, C. Cassan, J. P. Verdeil, J. David, and L. Pichon, "Power consumption trade-off between power amplifier obo, dpd, and clipping and filtering," in *2014 26th International Teletraffic Congress (ITC)*, Sept 2014, pp. 1–5.

[3] S. Wang, M. Roger, and C. Lelandais-Perrault, "Impacts of crest factor reduction and digital predistortion on linearity and power efficiency of power amplifiers," *IEEE Trans. Circuits Syst. II, Exp. Briefs*, pp. 1–1, 2018.

[4] S. Wang, M. A. Hussein, O. Venard, and G. Baudoin, "A novel algorithm for determining the structure of digital predistortion models," *IEEE Trans. Veh. Technol.*, pp. 1–1, 2018.

[5] X. B. Hu, M. Wang, and E. D. Paolo, "Calculating complete and exact pareto front for multiobjective optimization: A new deterministic approach for discrete problems," *IEEE Trans. Cybern.*, vol. 43, no. 3, pp. 1088–1101, June 2013.