Hardware-friendly Power Amplifier Linearization in Next-Generation Broadcasting Systems

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***Abstract*—It is essential to mitigate power amplifier (PA) non-linear (NL) effects to achieve energy-efficient radio communications. To restore the transmit signal quality, digital pre-distortion (DPD) is widely used. Recently, fast convergence DPD (FC-DPD) which offers good PA linearization has been proposed for next-generation broadcasting systems. However, it suffers from complexity issues and this paper addresses that drawback and we propose a low-complex version to make it hardware-friendly. We achieve significant complexity reduction by simplifying the Jacobian computation needed in the FC-DPD algorithm. This scheme can be extended to any memory-less PA model or a measured PA fitted to a polynomial model. We have provided proof that the proposed technique has linear complexity and the simulation results indicate that the proposed scheme achieves performance close to the FC-DPD algorithm. This method can be applied to other transmission systems as well.**

***Index Terms*—digital pre-distortion (DPD), ATSC 3.0, DVB-T2, energy efficiency, green communications**

I. Introduction

The main drawback of orthogonal frequency division multiplexing (OFDM) based digital terrestrial television (DTT) broadcasting systems which need to broadcast very high powers (up to $10\,\mathrm{kW}$ for a single transmitter) is their sensitivity to the non linear (NL) distortions caused by power amplifier (PA) located in the transmitter. This is a severe issue because the PA consumption amounts to 90% of the total transmitter consumption [1]. It is a serious challenge from the green communications perspective.

Therefore, any contemporary or next-generation DTT broadcasting system should operate the PA at a near saturation level, by opting for techniques that mitigate the NL effects of the PA on the transmit signal to restore its quality. This will facilitate the DTT network provider to broadcast the signal with high transmit power and thereby enhance its effective range of radio frequency (RF) coverage. In this paper, we consider two next-generation DTT broadcasting systems namely the European second generation Digital Video Broadcast-Territorial (DVB-T2) [2] and the more recent American next generation DTT (ATSC 3.0) [3]. This paper deals with digital pre-distortion (DPD), which is one of the most popular PA linearization techniques. Various methodologies of DPD for systems with or without PA memory effects exist in the literature [4].

Owing to the Bussgang theorem [5], an additional signal (also called a pre-distortion signal) can be generated for a PA's NL compensation in the baseband and added to the original information signal. However, this process needs a preliminary PA's characteristic estimation. Many of the recent DPD schemes have considered this perspective [6]–[9]. A DPD technique that relies on iterative compensation of error (ICE) has been proposed for non-linearly amplified OFDM signals in [6]. However, this scheme suffers from slow convergence. Another algorithm named fast convergence (FC)-DPD having a similar approach that can achieve very fast convergence has been recently proposed for broadcasting systems [7]. This algorithm is based on indirect learning architecture (ILA) and simplifies the DPD objective with a Taylor series approximation to convert it into a convex problem. Also, the search space for the convergence factor has been reduced and instead of directly solving the convex problem, a convergence factor value within its bounds offers a good trade-off between convergence speed and residual error value.

In this paper, we propose a novel low-complex scheme which is an improved version of FC-DPD that is suitable for hardware implementation. Our proposed scheme can be viewed as an extended work of the FC-DPD algorithm. The novelty of our work lies in linearizing the computation complexity of the FC block of the FC-DPD algorithm to simplify the computations of the elements in the Jacobian matrix in that FC block. We achieve this by converting the otherwise computationally expensive Jacobian matrix computation into a simple polynomial expression containing very few monomial terms. The simulation results show that our proposed scheme retains the features of FC-DPD in terms of linearization performance, fast convergence with linear complexity, and therefore a hardware-friendly one.

This paper is organized as follows: Section II reminds the OFDM system model, PA model, linearization problem, and some metrics related to PA linearization. Section III presents a brief overview of the fast convergence DPD (FC-DPD) scheme. The proposed scheme is presented in Section IV. In the same section, the proof of linearity computational complexity of our algorithm is provided. An analysis of PA linearization performance based on the simulation results is done in section V and then, the paper is concluded.

II. PA LINEARIZATION AND PERFORMANCE METRICS

Let $\mathbf{X}$ denote the M-ary QAM frequency-domain sequence of complex symbols $[X_0, X_1, ...X_{N-1}]$ transmitted over N subcarriers in a OFDM system. The output of an OFDM system is a discrete-time baseband signal $\mathbf{x} = [x_0, x_1, ...x_{N-1}]$ expressed as

$$x_k = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} X_n e^{2\pi j \frac{nk}{NT}}, \ 0 \le k \le NT-1, \quad (1)$$

where k stands for a discrete-time index, T is the OFDM symbol duration, and $j = \sqrt{-1}$. The discrete-time baseband signals are then later amplified using PA and OFDM signals are transmitted. Let us denote the discrete-time input and output vectors for PA as $\mathbf{x} = [x_0, x_1, \cdots, x_{N-1}]$ and $\mathbf{y} = [y_0, y_1, \cdots, y_{N-1}]$. We denote the PA amplification and pre-distortion functions as $\mathbb{A}$ and $\mathbb{PD}$ respectively. In a memory-less NL PA model with a complex soft envelope function $\mathbb{G}$, the output signal $\mathbf{y}$ can be represented as

$$\mathbf{y} = \mathbb{A}\big(\mathbf{x}\big) = \mathbb{G}\big(\mathbf{x}\big)e^{j\phi_{\mathbf{x}}}, \quad (2)$$

where, $\phi_{\mathbf{x}}$ is the phase vector of the input signal $\mathbf{x}$, i.e. $[\phi_0, \phi_1, \cdots, \phi_{N-1}]$ and ϕ_k is phase of x_k.

A. PA Linearization Problem

The general objective of any pre-distorter can be mathematically written as

$$\mathbf{y} = \mathbb{A}\big(\mathbb{PD}\big(\mathbf{x}\big)\big) = g_s \mathbb{L}\{\mathbf{x}\}, \quad (3)$$

where g_s is the small signal gain of the PA and $\mathbb{L}$ is a linear operator. If $\mathbb{L} = 1$ then the pre-distorter $\mathbb{PD}$ is the pre-inverse of PA i.e. $\mathbb{PD} = \mathbb{A}^{-1}$.

B. PA Model

In this paper, we consider the well-known Rapp model [10] commonly used to model solid-state PAs in broadcasting systems. For $0 \le k \le N-1$ and PA small signal gain g_s given as

$$y_k = \frac{g_s|x_k|}{\left(1 + \left(\frac{g_s|x_k|}{v_{sat}}\right)^{2p}\right)^{\frac{1}{2p}}}, \quad (4)$$

where g_s is the small signal gain of the PA, p is the knee factor and v_{sat} is the input saturation voltage of PA. However, our approach can be extended to any other memory-less PA model.

C. Performance Metrics

The main parameters considered in quantifying the performance of the proposed scheme in reducing out-of-band (OOB) and in-band (IB) distortions are discussed in the subsequent subsections.

1) Power spectral density for the OOB distortion analysis: The power spectral density (PSD) F of a single subcarrier OFDM signal is given as $F(f) = T\left(\frac{\sin(\pi f NT)}{\pi f NT}\right)^2$. The overall power spectral density of the modulated data is the sum of the power spectral densities of all the carriers.

2) Modulation error ratio for the IB distortion analysis: The modulation error ratio (MER) is the most widely used figure of merit in the broadcasting community as it indicates the IB signal deterioration even before the BER result turns bad. $\text{MER}(\mathbf{X}, \widehat{\mathbf{X}}) = 10\log_{10}\big(\|\mathbf{X}\|_2^2 / \|\mathbf{X} - \widehat{\mathbf{X}}\|_2^2\big)$, where $\mathbf{X}$ is the ideal symbol vector measured at the input of the amplifier and $\widehat{\mathbf{X}}$ is measured at the output of the PA.

III. FAST CONVERGENCE DIGITAL PRE-DISTORTION

The Bussgang theorem states that when a Gaussian stationary process passes through a memory-less NL device, the cross-correlation function of input and output is proportional to the auto-correlation function of input [5]

$$\mathbb{PD}(\mathbf{x}) = \mathbf{z} = \mathbf{x} + \mathbf{c}^{pd}, \quad (5)$$

where $\mathbf{z}$ is the predistorted signal and $\mathbf{c}^{pd}$ is the correction signal vector for DPD. Therefore, the DPD optimization problem can be mathematically formulated as

$$\mathbf{c}^{opt} = \arg\min_{\mathbf{z} \in \mathbb{R}^N} \quad \Big\| g_s\mathbf{x} - \mathbb{A}\big(\mathbf{z}\big) \Big\|_2^2. \quad (6)$$

We consider the FC-DPD technique that was recently proposed for broadcasting systems in [7]. In FC-DPD, the correction signal $\mathbf{c}^{pd}$ in (5) is constructed in an iterative manner with error compensation being done in time-domain. At the end of r^{th} iteration, the correction signal vector for the next iteration $\mathbf{c}_{r+1}^{pd}$, is computed through the following recurrence relation

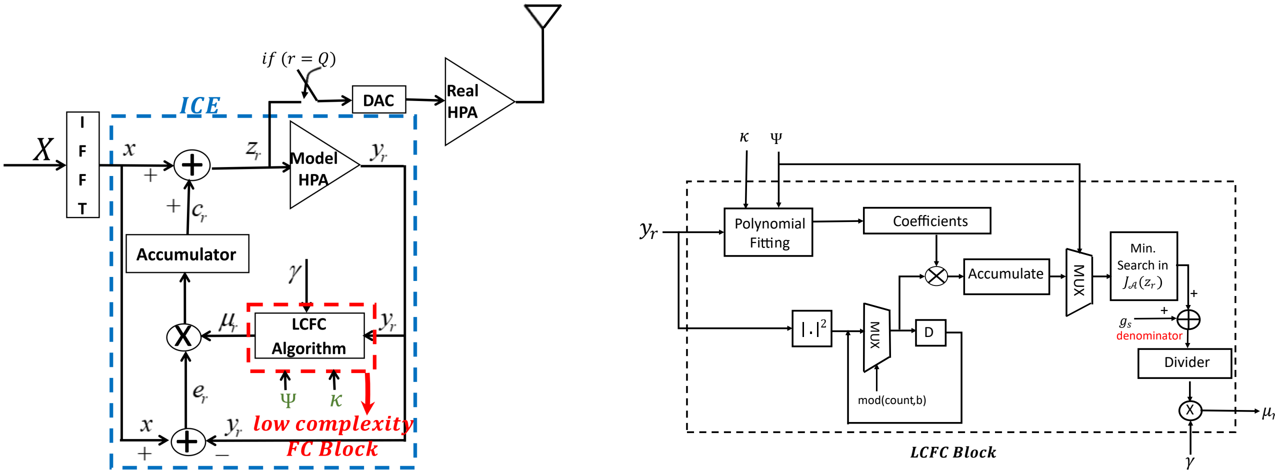
$$\mathbf{c}_{r+1}^{pd} = \mathbf{c}_r^{pd} + \mu_r^{pd}\mathbf{e}_r^{pd}, \ 1 \le r \le Q, \quad (7)$$

where $\mathbf{c}_1^{pd} = \mathbf{0}$, μ_r^{pd} ranging between $[0, 1]$, is the DPD convergence factor, $\mathbf{e}_r^{pd} = \mathbf{x} - \mathbb{A}\big(\mathbf{x} + \mathbf{c}_r^{pd}\big)$ is the error vector during the r^{th} iteration and Q is the number of ILA iterations. The varying convergence factor at each r^{th} iteration is calculated based on another parameter γ referred as tightness factor, also ranging between $[0, 1]$:

$$\mu_r^{pd} = \frac{\gamma}{\min(J_k) + \max(J_k)}, \ 1 \le r \le Q, \ 0 \le k \le N-1, \quad (8)$$

where J_k is the k^{th} diagonal element in the Jacobian matrix of the memory-less PA model output $\mathbb{A}\big(\mathbf{z}_r\big)$ w.r.t. $\mathbf{x}$.

$$J_{\mathcal{A}}(\mathbf{z}_r) = \frac{\partial \mathcal{A}\{\mathbf{z}_r\}}{\partial \mathbf{z}_r} = \begin{bmatrix} J_1 & 0 & \dots & 0 \\ 0 & J_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & J_N \end{bmatrix}_{N \times N}, \quad (9)$$



(a) LCFC-DPD scheme

(b) LCFC hardware block diagram

Figure 1: Block diagram of the proposed DPD method.

where $\mathbf{z}_r = \{z_1, z_2, \dots, z_i, \dots, z_N\}$ and $J_k = \frac{\partial \mathcal{A}\{z_k\}}{\partial z_k}$ is the k^{th} diagonal element of the Jacobian matrix and its general expression is given in [7] as

$$J_k = \frac{1}{2}\left(\frac{\partial \mathbb{G}(z_k)}{\partial |z_k|} + \frac{\mathbb{G}(z_k)}{|z_k|}\right),\ 0 \le k \le N-1. \quad (10)$$

The analytical expression of Jacobian of Rapp model PA is given by [7]

$$J_k = \frac{1}{2\left[1 + (\frac{g_s|z_i|}{v_{sat}})^{2p}\right]^{\frac{1}{2p}+1}} \left[2 + \left(\frac{g_s|z_i|}{v_{sat}}\right)^{2p}\right]. \quad (11)$$

FC-DPD has an extra block FC algorithm and includes an additional parameter, i.e., the tightness factor γ in order to optimize the convergence speed. In [7], it was proven that finding μ_r^{pd} is a convex problem and the FC-DPD algorithm has good convergence.

IV. The Proposed DPD Method

Although FC-DPD offers good linearization performance with fast convergence, it is evident from (11) requires estimating the $(2p)^{th}$ root on every discrete-time input signal x_k by following (4) has a non-linear asymptotic complexity of $\mathcal{O}\big((2\log_2 2p)(\log_2 \lambda)\big)$ using Newtons's method [11], λ is the number of desired precision bits. Then, we have operations involving $(1/2p)^{th}$ root as well. Therefore, finding μ_r^{pd} using state-of-the-art FC-DPD scheme requires N Jacobian matrix element computations at every r^{th} iteration. Such expensive computations at each iteration are very tedious to implement on the hardware. Hence, we propose a novel low-complex version of FC-DPD by computing the Jacobian with linear complexity which we refer to in this paper as low-complex FC-DPD (LCFC-DPD).

The polynomial model can be seen as the simplest way to model the behavior of a measured or modeled PA as a nonlinear system and is widely used for the memory-less modeling of PAs. It is well known that the Jacobian of a polynomial is another polynomial. From a hardware perspective, this straight-away avoids the need to perform the complicated $(2p)^{th}$ root and division operations.

The effect of even order terms on PA modeling and DPD have been investigated in [12]. In [13], odd-order polynomial approximation was compared to full-rank one and the conclusion is that both approaches give the same performance in terms of base-band modeling of PA non-linearity. Therefore, both these cases are considered in this paper.

The PA input/output relationship in the polynomial model for odd-order and full-rank (i.e. containing both odd-order and even-order terms) cases in terms of complex soft envelope function is

$$\hat{\mathbb{G}}(\mathbf{x}) = \begin{cases} \underbrace{\sum_{b=0}^{\Psi} a_{2b+1}|x_k|^{2b+1}}_{\hat{\mathbb{G}}_{or}(\mathbf{x})} & \text{if odd-order} \\ \underbrace{\sum_{b=0}^{\Psi} a_b|x_k|^{b+1}}_{\hat{\mathbb{G}}_{fr}(\mathbf{x})} & \text{if full-rank} \end{cases}, \quad (12)$$

where

- a_b and a_{2b+1} are the model's coefficients for odd-order and full-rank polynomial approximation respectively,
- $\hat{\mathbb{G}}_{or}$ is the complex soft envelope function for odd-order polynomial approximation, and
- $\hat{\mathbb{G}}_{fr}$ is the complex soft envelope function for full-rank order polynomial approximation.

In the next two subsections, we derive the analytical expression for the k^{th} diagonal element of the Jacobian matrix when odd-order and full-rank polynomial approximation is considered.

Subsequently, we prove that FC-DPD has linear computational complexity.

A. Analytical expression of a diagonal element of the Jacobian matrix

1) Odd-order approximation: Using (10) and (12), $\forall k \in [0, N-1]$ the odd-order approximated Jacobian expression is:

$$\hat{J}_k = \frac{1}{2}\left(\frac{\partial \hat{\mathbb{G}}_{or}(x_k)}{\partial |x_k|} + \frac{\hat{\mathbb{G}}_{or}(x_k)}{|x_k|}\right),$$
$$= \frac{a_{2b+1}}{2}\sum_{b=0}^{\Psi}\left((2b+1)|x_k|^{2b} + \frac{|x_k|^{2b+1}}{|x_k|}\right),$$
$$= \sum_{b=0}^{\Psi} a_{2b+1}(b+1)|x_k|^{2b}, \tag{13}$$
$$= \underbrace{a_1}_{c_{\text{I}}} + \underbrace{2a_3|x_k|^2}_{c_{\text{II}}} + \underbrace{\sum_{b=2}^{\Psi} a_{2b+1}(b+1)|x_k|^{2b}}_{c_{\text{III}}}. \tag{14}$$

2) Full-rank approximation: The full-rank expression is derived considering also the even-order coefficients. Using the complex gain function $\hat{\mathbb{G}}_f$ from (12), the full-rank approximated Jacobian expression can be stated as follows:

$$\begin{aligned}\hat{J}_k &= \frac{1}{2}\left(\frac{\partial \hat{\mathbb{G}}_{fr}(x_k)}{\partial |x_k|} + \frac{\hat{\mathbb{G}}_{fr}(x_k)}{|x_k|}\right),\\ &= \frac{1}{2}\sum_{b=0}^{\Psi} a_b(b+2)|x_k|^b.\end{aligned} \tag{15}$$

B. Proof of Linear Hardware Complexity of the Proposed Method

In the LCFC-DPD scheme, considering (13), the complexity in implementation will be due to c_{I}, c_{II}, and c_{III} respectively per input sample $x_k,\ 0 \le k \le (N-1)$ as shown in (14). Let us denote the number of real multiplications, real additions, and memory requirements as n_{mult}, n_{add} and ζ_{mem}, respectively. c_{I} term is only a scalar requiring no addition and multiplication operations and hence, $n_{\text{mult}}^{c_{\text{I}}} = 0, n_{\text{add}}^{c_{\text{I}}} = 0$. c_{II} term computations require two real multiplications, one real addition for $|x_k|^2$ and two real multiplications for scalar as well as polynomial coefficient a_3. Thus, c_{II} computational complexity is given by

$$n_{\text{mult}}^{c_{\text{II}}} = 2 + 2 = 4,\ n_{\text{add}}^{c_{\text{II}}} = 1. \tag{16}$$

We assume that $|x_k|^2$ is stored after c_{II} and then c_{III} computation requires $(\Psi - 1)$ multiplications to calculate other higher powers of $\left\{|x_k|^{2b}\right\}_{b=2}^{\Psi}$. Also, an additional multiplication is required to multiply the higher powers with coefficient $a_{2b+1}(b+1)$. Thus, c_{III} computational complexity is given by

$$n_{\text{mult}}^{c_{\text{III}}} = 2(\Psi - 1),\ n_{\text{add}}^{c_{\text{III}}} = (\Psi - 2). \tag{17}$$

Table I: Computational complexity per OFDM symbol with odd-order and full-rank polynomial approximation cases.

Approximation	Operation	Complexity	Weight
odd order	Multiplications	N	$(2\Psi + 2)$
	Additions	N	$(\Psi + 1)$
full rank	Multiplications	N	(4Ψ)
	Additions	N	$(2\Psi + 2)$

The overall computational complexity of the proposed DPD scheme for an OFDM signal with FFT size N and containing M OFDM symbols is

$$\begin{aligned}n_{\text{mult}} &= \left(n_{\text{mult}}^{c_{\text{I}}} + n_{\text{mult}}^{c_{\text{II}}} + n_{\text{mult}}^{c_{\text{III}}}\right)MN,\\ &= (2\Psi + 2)MN = \mathcal{O}(\Psi MN)\end{aligned} \tag{18}$$

$$\begin{aligned}n_{\text{add}} &= \left(n_{\text{add}}^{c_{\text{I}}} + n_{\text{add}}^{c_{\text{II}}} + n_{\text{add}}^{c_{\text{III}}} + n_{\text{add}}^{c_{\text{I}}+c_{\text{II}}+c_{\text{III}}}\right)MN,\\ &= \big(0 + 1 + (\Psi - 2) + 2\big)MN,\\ &= (\Psi + 1)MN = \mathcal{O}(\Psi MN)\end{aligned} \tag{19}$$

Similarly, ζ_{mem} memory is required to store all the polynomial coefficients $\{a_{2b+1}\}_{b=0}^{\Psi}$ and $|x_k|^2$ with linear complexity $\mathcal{O}(\Psi)$. Since $\Psi << MN$, we have $n_{\text{mult}} \approx \mathcal{O}(MN)$ and $n_{\text{add}} \approx \mathcal{O}(MN)$. This implies LCFC-DPD has linear hardware complexity and hence proved.

Analogous proof could be similarly done for full-rank expression. Similarly, the computational complexity for the full-rank case can be computed and we obtain

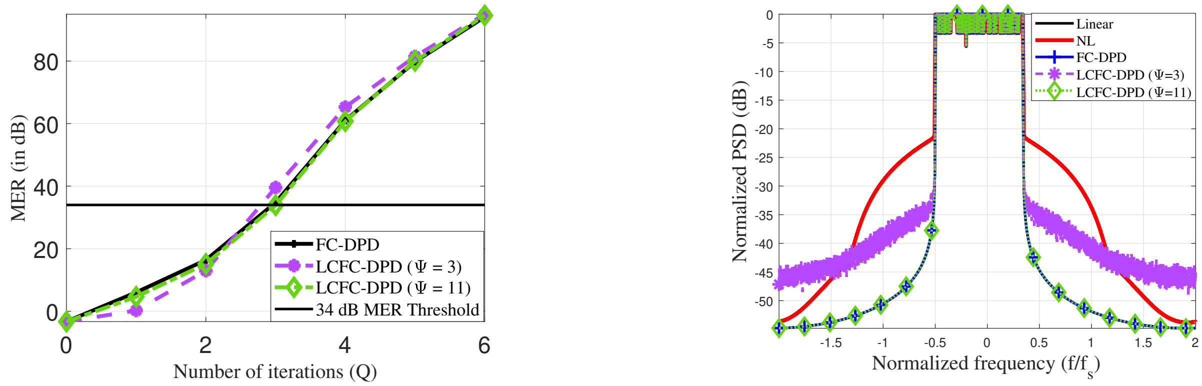
$$n_{\text{mult}} = 4\Psi MN = \mathcal{O}(\Psi MN), \tag{20}$$
$$n_{\text{add}} = 2(\Psi + 1)MN = \mathcal{O}(\Psi MN). \tag{21}$$

Thus, the overall hardware computational complexity per OFDM symbol for the proposed LCFC-DPD scheme with odd-order and full-rank polynomial approximations are enclosed in Table I.

The block diagram for the LCFC-DPD scheme along with the LCFC block is also illustrated in Fig. 1. This block shown in Fig. 1b has two additional inputs: polynomial order Ψ and polynomial fitting training set size κ.

V. Simulation Results

We consider Rapp model PA with $p = 2.25$, $v_{sat} = 1$, $g_s = 1$ for the simulations, unless specified otherwise. The simulations are done for the ATSC 3.0 system in 8k mode over 10^5 OFDM symbols with 256 QAM constellation (i.e. $M = 10^5$ and $N = 8192$). Both FC-DPD and LCFC-DPD use $\gamma = 0.7$. Since we confine to 8k mode, the analysis from our simulations is also applicable for the DVB-T2 system. In DVB-T transmission, an MER less than $34\,\text{dB}$ is deemed to induce transmission failure, and the same can be inferred in the case of DVB-T2 systems [14]. Moreover, a target value of MER above $34\,\text{dB}$ also assures that the transmitter RF coverage is almost similar to that of the theoretically achievable RF coverage limit.



(a) MER performance

(b) PSD performance

Figure 2: PSD performance of an ATSC 3.0 system with the LCFC-DPD algorithm in 8K mode for Rapp model PA, $p = 2.25$ at IBO=$5\,\mathrm{dB}$ over different orders of the odd-order polynomial approximation case with $\kappa = 100\%$.

A. Identification of necessary and sufficient NL polynomial approximation

It is expected that the proposed scheme will offer the same performance as the original FC-DPD method at higher values of polynomial order Ψ as shown in Fig. 2. But, from the complexity perspective, it is imperative to keep the Ψ as small as possible, i.e. $\Psi << MN$ to achieve linear complexity. To identify the optimal polynomial order, we initially choose $\kappa = 100\%$ (i.e full OFDM dataset). In section V-B, we identify the optimal κ as well to minimize the polynomial fitting hardware complexity.

The PA linearization problem objective in (6) maximizes the MER. Thus, we can predict that the MER performance of the proposed scheme approaches that of the original FC-DPD method with a small Ψ. Figures 2a and 2b validates the same, where LCFC-DPD with $\Psi = 3$ offers similar performance in terms of MER w.r.t. FC-DPD but requires higher Ψ to offer the same in terms of PSD. From Fig. 2b, we observe that $\Psi = 11$ is required. Therefore, $\Psi = 3$ is necessary and $\Psi = 11$ is sufficient to achieve both MER and PSD performances in the odd-order polynomial approximation case.

B. Impact of fitting order on the In-band (IB) and out-of-band (OOB) performance

The proposed low-complex FC-DPD scheme was run for $Q = 6$ with $\Psi = \{3, 11\}$, $\kappa = 10\%$ and the respective PSD plots are shown in Fig. 2b. In the legend of figures, "Linear", and "NL" indicate normalized PSD at the input and output of the Rapp model of PA, without any pre-distortion. Then, all remaining ones shown in the legend are for LCFC-DPD with different fitting orders. We observe that in the case of odd-order polynomial fitting, LCFC-DPD with $\Psi = 11$ approaches the MER performance of FC-DPD as shown in Fig 2a due to the decrease in approximation errors from the original FC-DPD method.

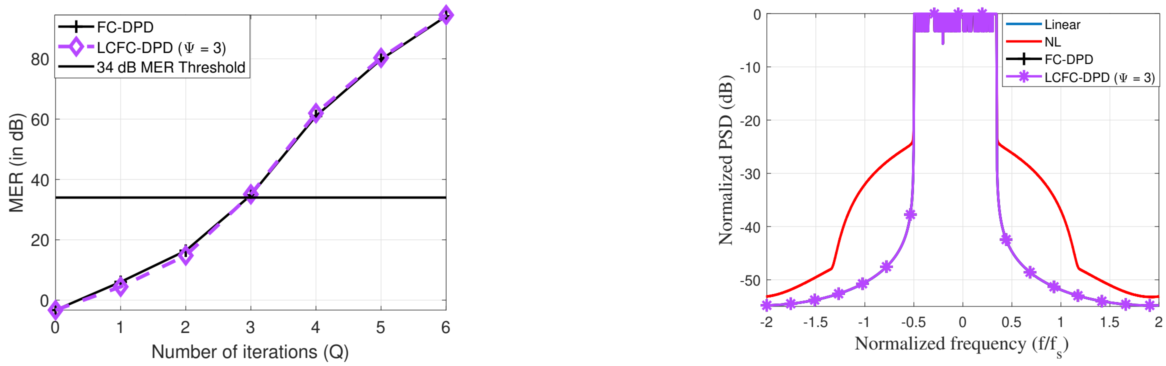
Table II: IB analysis at $Q = 4, 6$ & OOB analysis at the normalized frequency of 1, $Q = 6$ for different OFDM dataset sizes and Jacobian fitting order $\Psi = 11$

Dataset size κ (%)	MER Q=4	MER Q=6	Normalized PSD with FC-DPD†	Spectral regrowth w.r.t. linear case	Spectral degrowth w.r.t. NL case
5	33.73 dB	94.40 dB	−42.5 dB	9.40 dB	5.48 dB
10	**33.97 dB**	**94.52 dB**	**−51.86 dB**	**0.04 dB**	**14.84 dB**
20	33.89 dB	94.60 dB	−51.87 dB	0.03 dB	14.85 dB
100	33.73 dB	94.73 dB	−51.87 dB	0.03 dB	14.85 dB
Original	34.78 dB	94.12 dB	−51.88 dB	0.02 dB	14.86 dB

† Normalized PSDs in linear and NL cases at the normalized frequency of 1 are $-51.90\,\mathrm{dB}$ and $-37.02\,\mathrm{dB}$ respectively.

C. Low-complex extraction of the polynomial coefficients

Extraction of the polynomial coefficients $\{a_1, a_2, \cdots, a_\Psi\}$ in the proposed scheme requires an offline polynomial fitting over the dataset containing input OFDM data samples and their corresponding PA output samples. The size of the training dataset κ impacts the hardware complexity and memory due to polynomial fitting and can vary from a few samples to the full OFDM number of samples. The IB and OOB analysis for an 8k mode ATSC 3.0 system with Rapp model $p = 2.25$ is performed on the proposed scheme with various percentages of the OFDM dataset sizes and polynomial fitting order $\Psi = 11$ as shown in Table II. We notice that with $Q = 4$ LCFC-DPD achieves the target MER, i.e. $34\,\mathrm{dB}$ and with $Q = 6$ the spectral regrowth of the linearized signal with LCFC-DPD is less than $0.1\,\mathrm{dB}$ at the normalized frequency of 1. Additionally, we observe that $\kappa = 10\%$ of the OFDM dataset is necessary and sufficient to achieve the similar normalized PSD, spectral regrowth, and spectral degrowth performances to that of the original Jacobian (11) at a normalized frequency of 1. Thus, the hardware complexity of the polynomial fitting dataset in LCFC-DPD can be reduced by 90% and does not require any real-time processing when the PA conversion characteristics are known beforehand.



(a) MER performance

(b) PSD performance

Figure 3: MER and PSD performance of an ATSC 3.0 system with the LCFC-DPD algorithm in 8K mode for Rapp model PA, $p = 2.25$ at IBO=5 dB over order=3 in the full-rank polynomial approximation case with $\kappa = 10\%$.

D. Impact of full-rank polynomial fitting

As analyzed in sections V-A,V-B, and V-C, we performed the same in the case of full-rank polynomial fitting. We mention the final conclusions for the sake of brevity and it was found that LCFC-DPD with $\Psi = 3$ and $\kappa = 10\%$ is sufficient to achieve good IB and OOB performance. However, we show the MER and PSD plots in Fig. 3. From Table. I we observe that per OFDM symbol, while the full-rank case requires 98304 multiplications and 65536 additions, the odd-order case requires 196608 multiplications and 98304 additions. This implies that the full-rank case achieves the same FC-DPD performance with half the complexity compared to the odd-order case. This is due to the fact that in a full-rank polynomial model, the odd-order and even-order terms can effectively model the OOB spectral regrowth and IB distortion, respectively.

VI. Conclusion

This paper proposes a novel low-complex DPD technique to quickly linearize NL amplified signals in next-generation broadcasting systems distortion and can be applied to other transmission systems as well. This technique is based on polynomial approximation and offers linear computational complexity. The simulation results indicate that polynomials can be either odd-order or full-rank ones but the latter requires lower complexity than the former to achieve the state-of-the-art performance with fast convergence. This method can be extended to any memoryless PA model or a measured PA fitted to a polynomial model. Hardware implementation will be part of our future work.

VII. Acknowledgement

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References

[1] J. Wu, S. Rangan, and H. Zhang, *Green communications: theoretical fundamentals, algorithms, and applications*. CRC press, 2016.
[2] ETSI, *EN 302 755 Digital Video Broadcasting (DVB); Frame structure channel coding and modulation for a second generation digital terrestrial television broadcasting system (DVB-T2)*. ETSI, Sophia Antipolis, France, 2015. [Online]. Available: https://www.etsi.org/deliver/etsi_en/302700_302799/302755/01.03.01_40/en_302755v010301o.pdf
[3] ATSC, *ATSC Standard: Physical Layer Protocol*. ATSC, Washington, D.C, USA, 2023. [Online]. Available: https://prdatsc.wpenginepowered.com/wp-content/uploads/2023/04/A322-2023-03-Physical-Layer-Protocol.pdf
[4] P. B. Kenington, *High-Linearity RF Amplifier Design*. Artech House, Boston, MA, USA, 2000.
[5] J. J. Bussgang, "Crosscorrelation functions of amplitude-distorted gaussian signals," *Research Laboratory of Electronics Technical Report*, no. 216, 1952.
[6] O. A. Gouba and Y. Louët, "Digital predistortion expressed as an adding signal technique in ofdm context," in *2013 IEEE 11th International New Circuits and Systems Conference (NEWCAS)*. IEEE, 2013, pp. 1–4.
[7] S. S. K. C. Bulusu, H. Shaïek, and D. Roviras, "Hpa linearization for next generation broadcasting systems with fast convergence-digital predistortion," *IEEE Transactions on Broadcasting*, vol. 67, no. 3, pp. 776–790, 2021.
[8] R. Zayani, H. Shaïek, and D. Roviras, "Ping-pong joint optimization of papr reduction and hpa linearization in ofdm systems," *IEEE Transactions on Broadcasting*, vol. 65, no. 2, pp. 308–315, 2019.
[9] S. S. K. C. Bulusu, P. Susarla, H. Shaïek, D. Roviras, and O. Silvén, "Fast convergence joint optimization of papr reduction and digital predistortion in the next-generation broadcasting systems," in *To appear in 2013 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting(BMSB)*. IEEE, 2023.
[10] C. Rapp, "Effects of hpa nonlinearity on 4-dpsk-ofdm signal for digital sound broadcasting systems," *Eur. Conf. on Satellite Commun.*, pp. 179–184, Oct. 1991.
[11] S.-G. Chen and P. Hsieh, "Fast computation of the nth root," *Computers & Mathematics with Applications*, vol. 17, no. 10, pp. 1423–1427, 1989.
[12] L. Ding and G. Zhou, "Effects of even-order nonlinear terms on power amplifier modeling and predistortion linearization," *IEEE Transactions on Vehicular Technology*, vol. 53, no. 1, pp. 156–162, 2004.
[13] G. Zhou, H. Qian, L. Ding, and R. Raich, "On the baseband representation of a bandpass nonlinearity," *IEEE Transactions on Signal Processing*, vol. 53, no. 8, pp. 2953–2957, 2005.
[14] S. S. K. C. Bulusu, M. Crussière, J.-F. Hélard, R. Mounzer, Y. Nasser, O. Rousset, and A. Untersee, "Quasi-optimal tone reservation papr reduction algorithm for next generation broadcasting systems: A performance/complexity/latency tradeoff with testbed implementation," *IEEE Transactions on Broadcasting*, vol. 64, no. 4, pp. 883–899, 2018.