A Parameter Identification Algorithm for Multi-stage Digital Predistorter

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***Abstract*— In this paper, we propose an algorithm to identify the parameters of a multi-stage digital predistorter (PD). In multi-stage PD, digital predistortion (DPD) is implemented in two or more stages. Using the proposed algorithm each stage of the multi-stage PD can be identified separately by taking into account the contribution of all other stages. The algorithm is iterative and shown to converge after few system-level iterations. Through system level simulation, it has also been demonstrated that the proposed algorithm can be successfully used to identify the parameters of two-box, three-box or multi-stage memory polynomial (MP) predistorters. The performance of the proposed algorithm is evaluated by measuring the adjacent channel power ratio (ACPR) and error vector magnitude (EVM) at the output of power amplifier (PA) when a Long Term Evolution-Advanced (LTE-Advanced) signal is applied at the input.**

***Index Terms*— Multi-stage digital predistortion, indirect learning architecture, high power amplifiers**

I. Introduction

New transmission formats such as wideband code division multiple access (WCDMA) or orthogonal frequency division multiplexing (OFDM), with high peak-to-average power ratio (PAPR) and wide bandwidth, are increasingly being deployed for broadband wireless communication systems such as Universal Mobile Telecommunications System (UMTS), Long Term Evolution-Advanced (LTE-Advanced) etc.. However, when nonlinear high power amplifiers (PAs) are excited by such signals it causes severe distortion on the transmitted signal resulting in adjacent channel interference (spectral regrowth beyond the signal bandwidth) and in-band distortion (error vector magnitude degradation) [1]. To minimize the nonlinear distortions, it is desirable to operate the PA in its linear region i.e. with huge back off, but in this case, efficiency has to be compromised.

Many techniques for linearizing power amplifiers have been proposed in literature [1]: feedback, feedforward and predistortion. However digital predistortion (DPD) with its implementation flexibility and potential to achieve high performance improvement with significantly lower cost has been gaining widespread popularity. Consequently, DPD has been a frontrunner in solution for linearization of PAs in future multi-standard multi-band cognitive radios where reconfigurability will be of paramount importance [2].

A cascaded multi-stage structure has been frequently used in literature for DPD modeling. In this multi-stage structure one or more linear time invariant (LTI) systems are cascaded with a static memoryless nonlinearity [3]. One of the most used model to implement this multi-stage structure is the Wiener-Hammerstein (W-H) model, also called three-box model. In this model, an LTI system is connected in tandem to a static nonlinearity which is again connected to a LTI system as shown in [4]. Two-box models such as Wiener model in which an LTI system is connected in tandem to a static nonlinearity and Hammerstein model in which static nonlinearity is connected in tandem to a LTI system are special cases of the W-H model, have also been used in [5], [6]. To generalize cascaded multi-stage models, one can use for each stage a memory polynomial (MP) as given in [7]. Other configurations like generalized MP (GMP) [8] or 2D-Memory selective polynomial (2D-MSP) proposed in [9] can also be used to model each stage. Note that, LTI systems are special cases of the MP model considering only the first order nonlinearity [7].

However, one of the major problems associated with identifying the parameters of a cascaded multi-stage structure is the fact that the internal signals interconnecting the stages are inaccessible to measurements [10], [11]. Hence complex and tedious parameter estimation algorithms are usually used to identify the parameters of each stage of a multi-stage structure [5], [12]. These estimation algorithms are difficult to implement and have low correction capability and thus the usage of multi-stage structures for DPD implementation is restricted.

In this paper, we have tried to overcome the above drawback by proposing a new algorithm to identify the parameters of multi-stage PD [13]. In the proposed algorithm, each stage of multi-stage PD is identified separately by taking into account the contribution of all other stages. The algorithm is iterative and converges after few system-level iterations. It has also been demonstrated through simulation results that the proposed algorithm can be used for identification of two-box, three-box or multi-stage MP PD. The performance of the

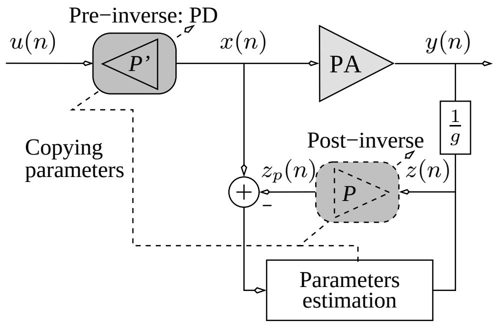

Fig. 1. Indirect Learning Architecture - ILA.

proposed algorithm is evaluated in terms of ACPR and EVM improvements using an LTE-Advanced signal. Furthermore, the impact of noise on the identification of the multi-stage PD using the proposed algorithm has also been investigated.

The remainder of this paper is organized as follows. Section II gives the brief description related to indirect learning architecture (ILA). Section III presents the proposed identification algorithm for multi-stage PD. In Section IV simulation results for proposed algorithm is presented and discussed. Finally Section V concludes the paper. In the following, the vectors and matrices are denoted by bold lowercase letters (eg. $\boldsymbol{a}$) and bold uppercase letters (eg. $\boldsymbol{A}$) respectively. The superscripts $(.)^*$, $(.)^T$ and $(.)^H$ denote the conjugate, the transpose and the conjugate transpose, respectively.

II. Indirect learning architecture (ILA)

In this section we briefly discuss the identification of parameters of a single stage PD using ILA.
A single stage PD identification using ILA is shown in Fig. 1. A post-inverse of the PA is identified and used as a PD. If the post-inverse is modeled as a MP, then its output can be written as [8]

$$z_p(n) = \sum_{k\in K}\sum_{l\in L} c_{pm}\Phi_{kl}[z(n)] \tag{1}$$

where $z(n) = \frac{y(n)}{g}$ is the input to the post-inverse block as shown in Fig. 1, K is the index array for nonlinearity and L is the index array for memory. c_{kl}, $k \in K$ and $l \in L$ are the complex coefficients and $\Phi_{kl}[z(n)] = z(n-l)|z(n-l)|^k$. The total number of coefficients is $J = \bar{\bar{K}}\bar{\bar{L}}$ with $\bar{\bar{X}}$ denoting the cardinality (number of elements) of X.
After convergence, we should have $z_p(n) = x(n)$ and hence $z(n) = u(n)$. For a total number of samples equal to N, we can write

$$\boldsymbol{z}_p = \boldsymbol{Z}\boldsymbol{c} \tag{2}$$

where $\boldsymbol{z}_p = [z_p(1), \ldots, z_p(N)]^T$, $\boldsymbol{c}$ is $J\times 1$ vector containing the set of coefficients c_{kl}, $\mathbf{Z}$ is $N\times J$ matrix containing $\Phi_{kl}[\boldsymbol{z}]$ where $\boldsymbol{z} = [z(1), \ldots, z(N)]^T$. The least square (LS) solution for (2) will be

$$\hat{\boldsymbol{c}} = (\mathbf{Z}^H\mathbf{Z})^{-1}\mathbf{Z}^H\boldsymbol{z}_p. \tag{3}$$

III. Proposed identification algorithm

The block diagram of the proposed identification algorithm is shown in Fig. 2. The proposed identification algorithm relies on the idea of gradually linearizing the PA. Similar to single stage PD identification using ILA, LS method is used identify the parameters of each stage of the multi-stage PD. We start by identifying a first stage which partially compensates the nonlinearity and/or memory of the PA. Then we identify the second stage which improves the linearity or compensate for the residual distortion of the new system constituted by the cascade of the first stage and the PA, then a third one to linearize the cascade of the second and first stages with the PA, etc.. Thus, the P_i stage is identified to improve the performance of the cascade of the $P_{i-1}, ..., P_1$ stages with the PA. The complexity of the identification algorithm, which depends on the number of parameters, will substantially decrease since only one stage is processed by iteration. This gain in complexity reduction is at the expense of the time of convergence, which may be longer.

It is important to note that after the insertion of last stage we have to re-identify the other stages as the behavior of the system might have changed due to the modification of the input waveform caused by the insertion of new stages [14], [15]. For ex. once P_i stage is identified, for subsequent identification of stage P_{i+1}, it will be considered as being part of a newly constituted system (stage $P_i, P_{i-1}, ..., P_1$, PA) as shown in Fig. 2. However once last stage is implemented, all the prior stages need to be re-identified. This process will optimize the identification of all stages and achieve the best possible solution[1] by simultaneously considering contribution from all the stages. Hence if M is the total number of stages, stage P_i is processed at the $(Mk+i)^{th}$ iteration, with $k = 0, 1, 2, 3, ...$ using stages $P_M, ..., P_{i-1}$. As shown later in simulation results the proposed algorithm converges after few system-level iterations.

The graphical description in Fig. 3 aids in explaining the steps for the identification of a three-stage PD (i.e. $M = 3$) model using the proposed algorithm. In the 1st iteration, Stage 1 is identified. In the 2nd iteration, Stage 2 is identified to optimize the performance of the cascade of Stage 1 with the PA. Similarly in the 3rd iteration, Stage 3 is identified to optimize the performance of the cascade of Stages 1 and 2 with the PA. However once Stage 3 is identified and implemented, in the 4th iteration Stage 1 is re-identified as the behavior of the system might have changed due to the modification of the input waveform caused by the insertion of Stages 2 and 3. This identification process is continued till the cascaded three-stage PD converges to the best possible solution.

IV. Simulation results

In this section, simulation results are presented for the proposed identification algorithm. A Wiener-Hammerstein model

[1]The best possible solution here refers to the identified PD model which achieves the best improvement in the performance of ACPR and EVM at the output of PA.

TABLE I

IDENTIFICATION OF TWO-BOX, THREE-BOX AND MULTI-STAGE MP PD USING THE PROPOSED ALGORITHM

Parameters	Without DPD	Two-Box PD (Wiener PD)	Two-Box PD (Hammerstein PD)	Three-Box PD (W-H PD)	Two-stage MP PD	Single-stage MP PD
ACPR U (dBc)	-50.7	-87.8	-74.7	-89.2	-98.2	-97
ACPR L (dBc)	-51.3	-86.8	-76.3	-87.0	-97.6	-96.9
EVM (%)	20.1	0.0467	0.049	0.029	0.009	0.029
Index array for Nonlinearity and Memory	NA	Stage 1: K=[0], L=[0 1 2 3 4 5 6] Stage 2: K=[0 2 4 6 8], L= [0]	Stage 1: K=[0 2 3 4 5 6 8], L=[0] Stage 2: K=[0], L= [0 1 2 3 4 5 6]	Stage 1: K=[0], L=[0 1 2 3 4 5 6] Stage 2: K=[0 2 3 4 5 6 8], L=[0] Stage 3: K=[0], L=[0 1 2 3 4 5 6]	Stage 1: K=[0 2 4], L=[0 1 2 3] Stage 2: K=[0 2 4 5 6 7], L= [0 1 2 4 6]	K=[0 1 2 3 4 5 6 7] L=[0 1 2 4 6 7]
Number of Coefficients (J)	NA	Stage 1: 7 Stage 2: 5	Stage 1: 7 Stage 2: 7	Stage 1: 7 Stage 2: 7 Stage 3: 7	Stage 1: 12 Stage 2: 30	48

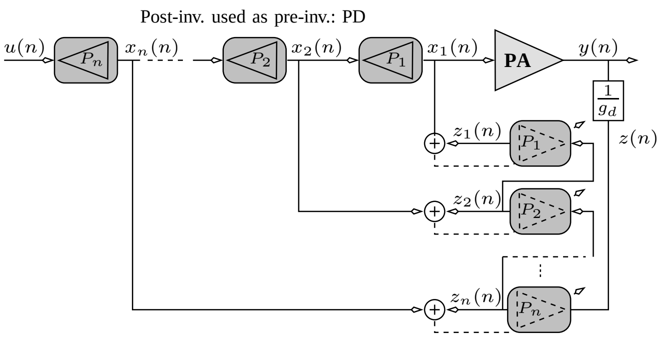

Fig. 2. Proposed identification algorithm for multi-stage PD.

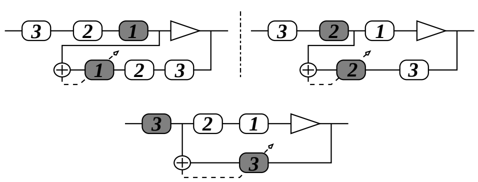

Fig. 3. Graphical illustration of the algorithm with three-stage PD.

as given in [7] is used as a reference PA for simulation. The PA is driven by an LTE-Advanced signal with bandwidth 10 MHz, sampling frequency 122.88 MHz and peak-to-average power ratio (PAPR) of approximately 11dB. During the simulation the nonlinearity order and/or memory depth of each stage of multi-stage PD are varied till the multi-stage PD achieves the best possible performance. Moreover to observe the impact of realistic noise floor on the PD identification for multi-stage PD, we also add low level white Gaussian noise at the input of post-inverse identification blocks. The performance with noise is demonstrated for signal-to-noise ratio (SNR) of 30dB.

Table I shows the results for the identification of two-box (Wiener and Hammerstein PD), three-box (W-H PD) and multi-stage MP PD using the proposed algorithm in absence of noise. The performance of multi-stage MP PD has been demonstrated by considering two-stage MP PD. For sake of completion, results of best-performing single-stage MP PD is also included. ACPR U and ACPR L measures the ratio of power in adjacent upper channel and lower channel of equivalent bandwidth with respect to the amount of power in the main channel respectively. K and L are vectors containing k and l values as given in (1). As seen from Table I, the proposed algorithm can be used to identify the parameters of two-box, three-box as well as multi-stage MP predistorters. All the multi-stage PD are able to achieve sufficient improvement in ACPR and EVM at the output of PA[2]. However, the multi-stage MP PD outperforms all the other PDs. Single stage MP PD achieves approximately same ACPR performance as multi-stage MP PD but requires large set of coefficients. It can also be seen from Table I that multi-stage MP PD requires lower non-linearity order and memory depth and as a consequence less number of coefficients compared to single-stage PD. Wiener PD and W-H PD are good compromise with fewer number of coefficients and sufficient improvement in ACPR and EVM performance at the output of PA.

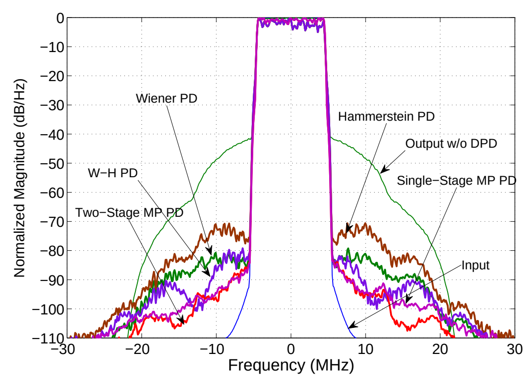

Fig. 4. The spectral regrowth suppression performance with Wiener PD, Hammerstein PD, W-H PD, multi-stage MP PD and single stage MP PD

Fig. 4 shows the spectral regrowth suppression performance with the proposed identification algorithm for Wiener PD, Hammerstein PD, W-H PD, two-stage MP PD and single stage MP PD in absence of noise. As observed all the identified multi-stage PD are able to achieve sufficient amount of spectral regrowth suppression. However the identified two-stage MP PD is able to achieve the best spectral regrowth suppression performance among all the different PD, hence proving to be more robust among all the different PD.

[2]Note that only the best values of ACPR and EVM over different system-level iterations are reported here.

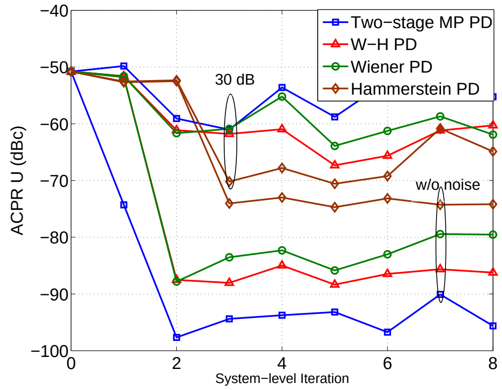

Fig. 5. ACPR Performance: System level Iterations

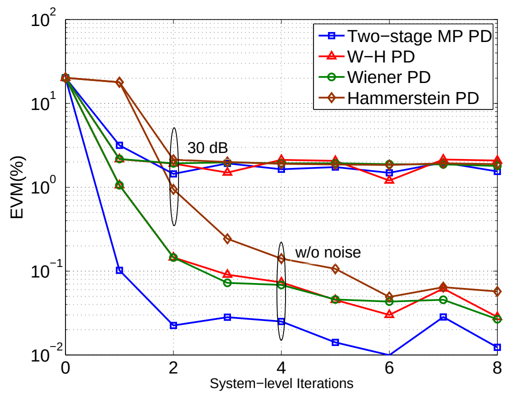

Fig. 6. EVM performance: System level Iterations

Fig. 5 and Fig. 6 shows the ACPR U and EVM performance of multi-stage PDs with the proposed identification algorithm for different system level iterations with (SNR=30dB) and without (w/o) noise. As observed the identification algorithm for all the multi-stage PD converges to the best possible solution after $2-3$ system level iterations. However it is quite obvious that two-stage MP PD outperforms all the other PD in absence of noise. Two-stage MP PD converges after 2nd system level iteration to achieve an ACPR of approximately -97dBc and EVM of approximately 0.02%. Hence two-stage MP PD is able to improve the ACPR performance by approximately 45dB in absence of noise. However, Hammerstein PD is more robust when noise is present in the identification process. Hammerstein PD achieves an ACPR improvement of approximately 20dB at 3rd system level iteration in presence of noise.

V. Conclusion

In this paper, a parameter identification algorithm for multi-stage PD is proposed. The proposed algorithm is shown to identify each stage of the multi-stage PD separately and system level convergence can be achieved in few iterations. The proposed algorithm is used to identify the parameters for Wiener PD, Hammerstein PD, W-H PD and multi-stage MP PD. The performance of the proposed algorithm is evaluated by measuring the ACPR and EVM at the output of the PA for an LTE-Advanced input signal. Furthermore, the impact of noise on the identification of the multi-stage PD using the proposed algorithm is also investigated. Simulation results demonstrated that two-stage MP PD outperformed all the other PD in absence of noise whereas Hammerstein PD achieved best ACPR improvement in presence of noise.

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