Partial Least Squares Identification of Multi Look-up Table Digital Predistortioners for Concurrent Dual-Band Envelope Tracking Power Amplifiers

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Abstract—This paper presents a technique to estimate the coefficients of a multi look-up table (LUT) digital predistortion (DPD) architecture based on the partial least squares (PLS) regression method. The proposed 3-D distributed memory LUTs (3D-DML) architecture is suitable for efficient FPGA implementation and compensates for the distortion arising in concurrent dual-band envelope tracking (ET) power amplifiers (PAs). On the one hand, a new variant of the Orthogonal Matching Pursuit (OMP) algorithm is proposed to properly select only the best LUTs of the DPD function in the forward path and thus reducing the number of required coefficients. On the other hand, the PLS regression method is proposed to address both the regularization problem of the coefficient estimation and, at the same time, reducing the number of coefficients to be estimated in the DPD feedback identification path. Moreover, by exploiting the orthogonality of the PLS transformed matrix, the computational complexity of the parameters’ identification can be significantly simplified. Experimental results will prove how it is possible to reduce the DPD complexity (i.e., the number of coefficients) in both forward and feedback paths while meeting the targeted linearity levels.

Index Terms—Envelope tracking, digital predistortion, look-up tables, partial least squares, power amplifier, principal component analysis.

I. INTRODUCTION

ENVELOPE tracking (ET) power amplifiers (PAs) have been proposed as an alternative to overcome low power efficiency amplification when using class-AB PAs operated with high back-off levels in order to accommodate the peak-to-average power ratio (PAPR) of the transmitted signal. The ET architecture requires an envelope modulator capable of efficiently amplifying the signal’s envelope over its whole bandwidth [1] (considered to be, according to the rule of thumb, 3 to 5 times the signal’s bandwidth). Since the overall ET efficiency is calculated as the product of the drain efficiency and the efficiency of the envelope modulator, several efforts have been devoted to design wide bandwidth envelope modulators [2], [3]. However, coping with wide bandwidth signals, concurrent dual-band (DB), multi-band or carrier aggregated signals with large separation between carriers is still a challenge to guarantee efficient amplification using ET PAs. Several alternatives to deal with the existing trade-off between signal bandwidth and efficiency in ET PAs have been proposed, such as considering the use of slower envelopes to dynamically supply the PA [4]–[6].

Focusing on concurrent DB or non-contiguous carrier aggregation transmissions with certain separation between carriers, solutions based on the use of slow envelope versions of the original signal’s envelope to dynamically supply the PA were proposed in literature. However, unwanted distortion effects related to the slow envelope used to dynamically supply the PA as well as the inherent PA nonlinear behavior had to be compensated in order to comply with the required ACPR and NMSE levels. Therefore, the 3-D behavioral models for linearizing concurrent dual-band envelope tracking PAs were proposed [7]–[9].

The number of coefficients required by these 3D behavioral models grows exponentially when considering memory effects. This negatively impacts on the least squares (LS) estimation because it not only increases the computational complexity but also drives to over-fitting and uncertainty. In addition, when targeting an FPGA implementation, the DPD function in forward path should be designed as simple as possible (i.e., including the minimum and most relevant basis functions) to save as many hardware logic resources and memory as possible.

With this goal in mind, in the PAWR2018 paper [10], we took the 3-D distributed memory polynomial DPD model (proposed in [7]) to compensate for the in-band and cross-band intermodulation distortion as well as for the slow-envelope dependent distortion that appears when supplying the PA with a slower version of the DB envelope) and presented a new multi-LUT architecture suitable for FPGA implementation. The proposed 3-D distributed memory LUT (3D-DML) model followed a multi-LUT architecture with linear/bilinear interpolation and extrapolation as defined by Molina et al. in [11]. In addition, in order to properly select the minimum number of LUTs of the 3D-DML model to meet the required linearity specifications, a modified version of the Orthogonal Matching Pursuit (OMP) algorithm [12], named OMP-LUT, was presented in [10].

Despite the fact that with the OMP-LUT algorithm it is possible to efficiently reduce the number of required LUTs in...
the forward path DPD function, while still being compliant with the linearity specifications, a proper well-conditioned identification of the LUTs coefficients still cannot be guaranteed. The reason is that with the OMP-LUT algorithm in [10] we have to include, for the sake of completeness, some basis functions with low relevance, which may lead to a rank deficient LS identification.

Several efforts have been made to solve the ill-conditioning problem such as the Ridge regression, consisting in a $\ell_2$-norm regularization [13]. Alternatively, reducing the order of the DPD model by properly selecting the most significant basis functions or creating a new set of orthogonal basis functions has beneficial effects in both the computational complexity and in the conditioning of the data matrices. The singular value decomposition (SVD) [14]–[17] or the principal component analysis (PCA) technique [18], [19] is commonly used for extracting the dominant eigenvalues/eigenvectors and thus reducing the order of the DPD function.

In this paper, unlike in [10], where the emphasis was put in reducing the complexity of the DPD function in the forward path, we focus on the feedback identification/adaptation path. The idea is conceptualized in Fig. 1. The objective is twofold, on the one hand we want to ensure a proper, well-conditioned parameter identification while, on the other hand, we want to further decrease the number of coefficients to be estimated. For that reason we propose the use of the partial least squares (PLS) regression method [20] for extracting the DPD coefficients of the 3D-DML DPD. Similarly to PCA, the PLS-based method converts the original basis functions into a new data matrix composed of orthogonal basis functions. Moreover, some additional model pruning can be applied to the new transformed matrix, which will reduce the number of parameters to estimate. The accuracy and robustness of the PLS method will be properly compared to the one based on PCA.

Therefore, the remainder of this paper is organized as follows. To create a self-contained paper for the reader, Section II summarizes the 3D-DML model and the proposed best LUTs selection method presented in the PAWR2018 paper [10] to design the DPD function in the forward DPD path. In Section III, the identification/adaptation subsystem based on using the PLS regression method to further reduce the number of the parameters required for a robust identification is presented. Section IV describes the experimental test bench, while Section V shows a comparison between PLSC and PCA to evaluate the reduction ratio that can be applied in the number of coefficients without suffering significant degradation in the DPD linearization performance. Finally, conclusions are given in Section VI.

II. FORWARD DPD PATH

A. 3D-DML Digital Predistorter

The general block diagram of the closed-loop DPD system architecture is depicted in Fig. 1. For DB ET PAs, this architecture has to be replicated to predistort the transmitted signals at each one of the bands, as described in [7].

In order to simplify the DPD for DB ET PAs and targeting an FPGA implementation, in [10] we proposed the 3D-DML DPD model that uses LUTs with linear/bilinear interpolation and extrapolation. The 3D-DML DPD model for the signal in Band 1 is defined as:

$$ x_1[n] = \sum_{i=0}^{N_1-1} u_1[n - \tau_i u_1]\left| f_{\Phi_1,i}ight| + \sum_{i=1}^{N_2-1} M_2 \sum_{j=1}^{N_2-1} u_1[n] f_{\Phi_1,i,j}\left| u_1[n - \tau_i u_1], u_2[n - \tau_j u_2]\right| + \sum_{i=1}^{N_3-1} K_3 \sum_{k=1}^{K_3} u_1[n] f_{\Phi_1,i,k}\left| u_1[n - \tau_i u_1], E[n - \tau_k]\right| $$

where $N_1$, $N_2$ and $N_3$ are the numbers of delays of the input signal $u_1[n]$ at each branch; $M_2$ is the number of delays of the interference signal $u_2[n]$; $K_3$ is the number of delays of the supply envelope $E[n]$; $\tau_i$, $\tau_j$ and $\tau_k$ (with $\tau_u,u_2,e \in Z$ and $\tau_u,u_2,e = 0$) are the most significant sparse delays of the input ($u_1[n]$), interference signal ($u_2[n]$) and envelope ($E[n]$). Moreover, following the LUT interpolation and extrapolation concept in [11], $f_{\Phi_1,i,j}(u_1)$ in (1) represents a 1-D LUT and is a piecewise linear complex function defined as the linear combination of $N$ basis functions; while $f_{\Phi_1,i,k}(u_1,u_2)$ or $f_{\Phi_1,i,k}(u_1,E)$ in (1) are 2-D LUTs defined by a piecewise bilinear complex function. Further details on the bilinear interpolation and extrapolation can be found in [10], [11].

Analogously, the DPD function for Band 2 can be defined as in (1) but with $u_2[n]$ and $u_1[n]$ being the input and interfering signal, respectively.

B. Best LUTs Selection Method (OMP-LUT)

In the 3D-DML DPD model, the required number of coefficients to compensate for the in-band, cross-band intermodulation distortion and the slow-envelope dependent distortion in ET PAs is significantly high. This leads to an increase of the system’s computational complexity. Besides, the sparse data of LUT-based DPD model drives the system to over-fitting and uncertainty. Fortunately, this sparsity of the DPD models can be exploited to reduce the number of required basis functions.

In order to decrease the number of basis functions of the 3D-DML DPD model (while still being able to meet the desired linearity levels), the OMP-LUT method was proposed.
in [10] to select the most relevant LUTs conforming the DPD function. First, the OMP-LUT algorithm determines the weight of each LUT in the model according to the frequency of appearance of its components and the position in the OMP list of the most relevant basis functions (more details on the general OMP-BIC algorithm can be found in [12]). Then, the OMP-LUT algorithm selects the minimum number of LUTs with the highest weights that complies with the imposed linearity requirements.

For the sake of completeness, the results obtained with the OMP-LUT method in [10], are listed again in Table I and discussed in Section V.

III. FEEDBACK IDENTIFICATION/ADAPTATION PATH

The Least Squares (LS) coefficient estimation/adaptation of a general DPD is depicted in Fig. 1, where the DPD coefficients can be iteratively found by following a direct learning approach:

\[ w_{i+1} = w_i + \lambda (U^H U)^{-1} U^H e \]

with \( w_i \) being the vector of coefficients of the DPD model at the \( i^{th} \) iteration, where \( U \) is the data matrix containing the basis functions describing the DPD model and \( \lambda \) is the learning-rate parameter. Finally, the identification error is defined as \( e = y - G_0 u \), where \( y \) is the PA output signal, \( G_0 \) is the desired linear gain of the PA and \( u \) is the input signal.

As shown in (2), typically, the Moore-Penrose inverse (i.e., \((U^H U)^{-1} U^H\)) is used to solve the LS identification. However, when the correlation matrix \((U^H U)\) is ill-conditioned, the values of the estimated coefficients are no longer reliable. Several regularization techniques [21] can be found in literature to address this problem. Among them, we propose an approach based on the PLS regression method that not only enhances the conditioning of the estimation but also allows to reduce the number of coefficients to be estimated.

A. Partial Least Squares (PLS)

PLS is a popular statistical technique used in many different applications, such as regression, classification, dimension reduction and modeling [20]. In particular, in this paper we employ PLS as a dimension reduction technique, similarly to the work presented in [19] where the PCA technique was used for model order reduction. Both PLS and PCA methods construct new components that are linear combinations of the original basis functions but, while PCA obtains new components that maximize their own variance, PLS finds linear combinations of the original basis functions that maximize the covariance between the new components and the output vector (or reference signal). As it will be shown in Section V, this enables PLS to outperform PCA in applications such as PA behavioral modeling and DPD linearization, since PLS improves the accuracy of the estimation of the output vector.

Let us consider a non-square tall data matrix \( X \) containing the basis functions that describes the PA nonlinear behavior and memory effects (to be used for either PA behavioral modeling or DPD linearization). By using PLS, the \( M \) original basis functions \( x_i = (x_i[0], x_i[1], \cdots, x_i[N-1])^T \), with \( i = 1, 2, \cdots, M \), of the data matrix \( X = (x_1, x_2, \cdots, x_M) \) are converted, through a transformation matrix \( P \), into \( L \) \((L \leq M)\) new orthogonal components \( \hat{x}_j \), with \( j = 1, 2, \cdots, L \), of the transformed data matrix \( \hat{X} = (\hat{x}_1, \hat{x}_2, \cdots, \hat{x}_L) \). The relation between the \( N \times M \) original data matrix \( X \) and the \( N \times L \) transformed one \( \hat{X} \) is defined by the following linear combination,

\[ \hat{X} = XP \]

with \( P \) being the \( M \times L \) transformation matrix and \( N \) being the number data samples. The columns of the transformed matrix \( \hat{X} \) are sorted according to their contribution to maximize the covariance between the new components and the output vector \( y \). By using the iterative SIMPLS algorithm described in [22] we can obtain the transformation matrix \( P \). As long as the signal statistics do not change significantly, the transformation matrix \( P \) can be calculated off-line only once.

B. Coefficient Estimation/Adaptation

For simplicity and without loss of generality, we will now consider the estimation of the coefficients of a PA behavioral model \( w_{pa} \). Following the notation in Fig. 1, the estimated output vector \( \hat{y} \) of a PA behavioral model can be defined as

\[ \hat{y} = Xw_{pa} \]

with \( w_{pa} \) being the vector of estimated coefficients and \( X \) is the data matrix containing the basis functions of the PA model. The coefficients are estimated as

\[ w_{pa} = (X^H X)^{-1} X^H y \]

where \( y = (y[0], y[1], \cdots, y[N-1])^T \) is the \( N \times 1 \) vector of measured PA output data. The estimation of the coefficients \( w_{pa} \) of the DPD function is performed iteratively in a similar way (see Fig. 1) with \( U \) being the data matrix containing the basis functions for DPD.

In both cases, if the correlation matrix is ill-conditioned, the Moore-Penrose inverse will provide an inaccurate solution. Most of the published DPD solutions based on Matlab designs solve this problem by using the Matlab’s backslash operator (\( \backslash \)), where some kind of regularization (not specified by Mathworks) is applied. As an alternative to Matlab’s backslash solution and targeting an FPGA implementation, PLS can be used to both solve the ill-conditioning problem and reduce the number of basis functions.

The resulting PLS transformed matrix \( \hat{X} \) is composed by \( L \) \((L \leq M)\) orthogonal components, which significantly simplifies the parameter extraction. Thanks to the orthogonality of the components of \( \hat{X} \), the matrix inversion of the correlation matrix in (5) can be simplified as follows,

\[ (X^H X)^{-1} = \left( \sigma_1^{-1}, \sigma_2^{-1}, \cdots, \sigma_L^{-1} \right) I \]

where \( \sigma_j \), with \( j = 1, 2, \cdots, L \), is the \( \ell_2 \)-norm squared of the new basis function \( x_j = (x_j[0], x_j[1], \cdots, x_j[N-1])^T \) of the new transformed matrix \( \hat{X} = (\hat{x}_1, \hat{x}_2, \cdots, \hat{x}_L) \) and \( I \) is the
identity matrix. Therefore, the computation of each one of the new (transformed) coefficients \( \tilde{w}_j \), with \( j = 1, 2, \ldots, L \), can be calculated independently as follows

\[
\tilde{w}_j = \sigma_j^{-1} x_j^H y
\]

(7)

Once the \( L \times 1 \) vector of transformed coefficients \( \tilde{w}_{\text{PLS}} = (\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_L)^T \) is identified, it is possible to calculate the new original \( M \times 1 \) vector of coefficients as follows

\[
w_{\text{PLS}} = P \tilde{w}_{\text{PLS}}
\]

(8)

with \( P \) being the \( M \times L \) PLS transformation matrix.

IV. EXPERIMENTAL TEST BENCH

The evaluation of the LUT-based DPD for concurrent dual-band envelope tracking was carried out in the remoteUPCLab testbed depicted in Fig. 2. In collaboration with IEEE MTT-S and Rohde & Schwarz (R&S), our research group assembled the remoteUPCLab testbed in the framework of the IMS2017 DPD student design competition [23]. It consisted of a PC running MATLAB and an FTP server to allow worldwide users to connect to the equipment. The functioning is described in the following.

The remoteUPCLab server receives the incoming baseband I/Q waveforms and an appropriate delay-compensated supply waveform from a remote user. These are both downloaded into the R&S SMW200A vector signal generator (VSG) that generates \( i \) the I/Q signals being RF up converted to deliver the PA input signal (i.e. through the VSG I/Q modulator) and \( e \) the EVM supply modulator input signal. The R&S FSW8 signal and spectrum analyzer (SSA) is in charge of RF down conversion and data acquisition of the waveform at the output of the PA, whose I/Q data will be sent back to the remote user for DPD processing. The device under test (DUT) consists in a Texas Instruments LM3290-91-EVM ET board that includes a Skyworks SKY776621 4G handset PA operated at 1950 MHz. The PA is operating with a dual-band signal composed by two OFDM signals whose center frequency is spaced 80 MHz and that feature 10 MHz and 5 MHz bandwidth. The baseband clock that is employed in the signal processing operations is 122.88 MHz which corresponds also to the I/Q A/D and D/A sampling frequencies (no oversampling is applied). The peak output power level from the SKY77621 PA is limited to approximately 1 W. The settings in the signal analyzer (reference level and input attenuation) are set in such a way as not to distort the measured signal even for the highest peak power levels allowed.

V. EXPERIMENTAL RESULTS

In [10], we proposed a modification of the OMP algorithm, named OMP-LUT, that allows searching for the most relevant LUTs of the 3D-DML DPD function in the forward path. Three different selection methods applied to the original data matrix (composed of 223 basis functions) in the forward path were compared in order to show the model order reduction capabilities while meeting the linearity specifications (set at \(-45\) dBc of ACPR):

\begin{table}[h]
\centering
\caption{Comparison of Different OMP Coefficient Selection Methods for 3D-DML DPD}
\begin{tabular}{|c|c|c|c|c|c|c|}
\hline
\hline
(a) No OMP & 23.1 & 19.0 & B1: -36.5 & B1: -45.6 & B1: 85 & \hline
(c) OMP-LUT & 23.0 & 18.7 & B2: -37.5 & B2: -45.3 & B2: 92 & \\
\hline
\end{tabular}
\end{table}

a) No OMP: no proper search is carried out, the LUT selection is done by adding consecutive memory terms of both input signals and the slow envelope. It is likely that with this straightforward method to build the data matrix (no requirement or constraint is applied to select LUTs), some basis functions will be highly correlated among them.

b) OMP-col: selection of the best basis functions (or columns of the data matrix) using the OMP-BIC algorithm without taking into account to which LUT they belong to, and thus, without caring if the resulting selected basis correspond to complete LUTs or not. The output of the search are the best columns (i.e. the most relevant basis functions) of the data matrix. With the OMP-col, we are implicitly avoiding the ill-conditioning problem by selecting the most relevant basis functions.

c) OMP-LUT: selection of the best LUTs using the modified version of the OMP-BIC algorithm. The output of the search are the best complete LUTs of the data matrix. For the sake of completeness some basis functions with low relevance have to be added to complete the LUT structure and this may later contribute to introduce uncertainty in the estimation of the coefficients.

The linearity and power efficiency values obtained when reducing the coefficients of the 3D-DML DPD model in the forward path using the aforementioned methods were already presented in [10]. To make this paper self-contained we list again Table I, showing that to reach \(-45\) dB of ACPR and achieve equivalent NMSE, Pout and power efficiency values, the OMP-LUT selection method uses a smaller number of LUTs, and thus coefficients, in the forward path DPD function, than the other two methods.

Then, starting from the reduced set of coefficients obtained for the DPD function in the forward path in [10], in this paper we focus on improving the conditioning of the estimation as well as reducing the number of parameters to be estimated in the feedback identification/adaptation path. For simplicity and without loss of generality, the advantages of the PLS-based estimation will be highlighted considering the extraction of the coefficients of the 3D-DML PA behavioral model instead of the 3D-DML DPD model.

As explained before, in order to extract the coefficients of the DPD function (based on LUTs) in the forward path, the Moore-Penrose inverse is commonly used to solve the LS regression. However, if the resulting order reduced matrix is
not well-conditioned, then the coefficient estimation may lead to an inaccurate solution. In the particular case of the OMP-col selection, since all the basis functions were properly selected, the LS estimation will be perfectly conditioned. However, in the OMP-LUT case, because the objective is to obtain an integer number of complete LUTs we have to include some of the basis functions (i.e., columns) that make the LS estimation rank deficient. To illustrate this, Table II shows the results of PA behavioral modeling in terms of NMSE and ACEPR for the three selection methods when considering the Moore-Penrose inverse (MP-LS) and the Matlab’s backslash (\) operations.

It can be observed that in the case of the OMP-LUT basis selection, the MP-LS cannot provide an accurate estimation, while the Matlab’s backslash operator can.

As an alternative to the backslash operator, we propose the PLS algorithm to both improve the conditioning of the correlation matrix and reduce the number of coefficients of the estimation. In addition, we compare the accuracy versus coefficient reduction between the PLS and PCA techniques. The figures Fig. 3-Fig. 5 show the NMSE and ACEPR evolution when considering different numbers of coefficients in the identification for the following test cases: a) No-OMP, b) OMP-col and c) OMP-LUT, respectively. In all three cases, we can see that the PLS technique is more robust than PCA in terms of NMSE and ACEPR degradation when reducing the number of coefficients of the estimation (coefficients of the transformed basis). The reason for this is that PLS, unlike PCA, takes also into account the information of the output signal for creating the transformation matrix.

In case a) No-OMP in Fig. 3, there are two types of NMSE and ACEPR degradation, when the number of identification components is too small and also when the full basis of components is considered. The latter degradation is due to the fact that the correlation matrix is ill-conditioned when considering the full basis of new components because we are including the ones that are expendable. Eliminating the less relevant columns (components) produces a regularization effect, which results in a new well-conditioned basis with less coefficients to estimate. Similarly, in case c) OMP-LUT in Fig. 5 we can observe the same behavior involving NMSE and ACEPR degradation due to excess of coefficient reduction or due to the ill-conditioned estimation for an excess of linear dependent components. Instead, in case b) OMP-col in Fig. 4, thanks to the proper basis selection performed by the OMP-BIC algorithm, no ill-condition problem is observed at high
The advantage of using the PLS technique for the coefficients estimation when considering the case of the OMP-LUT basis selection is summarized in Table III. Thanks to PLS, we can reduce the number of coefficients to be estimated almost without losing accuracy in the identification. In particular (see Table III), around 35% for Band 1 and 34% for Band 2 of reduction in the number of coefficients can be considered at the expenses of a loss of identification performance (in terms of NMSE and ACEPR) of less than 0.5% in the worst case.

VI. CONCLUSION

In this paper, the PLS regression method is proposed to address the ill-conditioning problem of the DPD coefficient estimation. To validate the proposed PLS method, we considered the 3D-DML DPD model presented in [10]. The 3D-DML model is a multi-LUT design for FPGA implementation that is capable of coping with the nonlinear distortion arising in an ET PA under a concurrent DB transmission. The proposed 3D-DML DPD was designed by properly selecting the most relevant LUTs (to at least meet the -45 dBc of ACPR) by using a modified version of the OMP algorithm (i.e., OMP-LUT).
With PLS, a set of new components (i.e. the new basis) is generated from the original basis functions. By properly selecting the most relevant components from the set, it is possible to guarantee a well-conditioned identification while reducing the number of estimated parameters without loss of accuracy. In addition, thanks to the orthogonality among the components of the new basis, the matrix inversion operation is significantly simplified and, as shown in (7), each of the DPD coefficients can be estimated independently.

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