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

Quynh Anh Pham, *Student Member, IEEE,* David López–Bueno, *Member, IEEE,* Teng Wang, *Member, IEEE,* Gabriel Montoro, *Member, IEEE,* and Pere L. Gilabert, *Senior Member, IEEE*

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's 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 ℓ_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 PLS 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
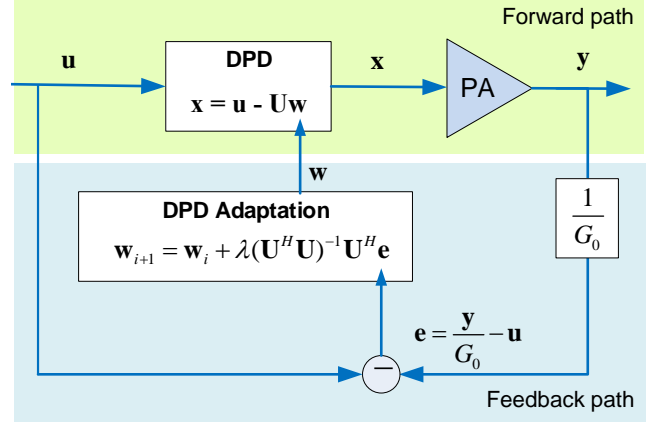

Fig. 1. Block diagram of a closed-loop DPD system following a direct learning approach.

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:

$$x_1[n] = \sum_{i=0}^{N_1-1} u_1[n-\tau_i^{u_1}] f_{\overline{\Phi}_{1,i}}\left(\left|u_1[n-\tau_i^{u_1}]\right|\right)+$$
$$\sum_{i=1}^{N_2-1}\sum_{j=1}^{M_2-1} u_1[n] f_{\overline{\Phi}_{1,i,j}}\left(\left|u_1[n-\tau_i^{u_1}]\right|,\left|u_2[n-\tau_j^{u_2}]\right|\right)+$$
$$\sum_{i=1}^{N_3-1}\sum_{k=1}^{K_3-1} u_1[n] f_{\overline{\Phi}_{1,i,k}}\left(\left|u_1[n-\tau_i^{u_1}]\right|, E[n-\tau_k^e]\right) \qquad (1)$$

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 $E[n]$; τ^{u_1}, τ^{u_2} and τ^e (with $\tau^{u_1,u_2,e} \in \mathbf{Z}$ and $\tau_0^{u_1,u_2,e} = 0$) 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], $f_{\overline{\Phi}_{1,i}}(u_1)$ in (1) represents a 1-D LUT and is a piecewise linear complex function defined as the linear combination of N basis functions; while $f_{\overline{\Phi}_{1,i,j}}(u_1, u_2)$ or $f_{\overline{\Phi}_{1,i,k}}(u_1, E)$ 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:

$$\mathbf{w}_{\text{DPD}}^{i+1} = \mathbf{w}_{\text{DPD}}^{i} + \lambda (\mathbf{U}^H \mathbf{U})^{-1} \mathbf{U}^H \mathbf{e} \tag{2}$$

with $\mathbf{w}_{\text{DPD}}^{i}$ being the vector of coefficients of the DPD model at the ith iteration, where $\mathbf{U}$ is the data matrix containing the basis functions describing the DPD model and λ is the learning-rate parameter. Finally, the identification error is defined as $\mathbf{e} = \dfrac{\mathbf{y}}{G_0} - \mathbf{u}$, where $\mathbf{y}$ is the PA output signal, G_0 is the desired linear gain of the PA and $\mathbf{u}$ is the input signal.

As shown in (2), typically, the Moore-Penrose inverse (i.e., $(\mathbf{U}^H \mathbf{U})^{-1} \mathbf{U}^H$) is used to solve the LS identification. However, when the correlation matrix ($\mathbf{U}^H \mathbf{U}$) 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 $\mathbf{X}$ 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 $\mathbf{x}_i = (x_i[0], x_i[1], \cdots, x_i[N-1])^T$, with $i = 1, 2, \cdots, M$, of the data matrix $\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_M)$ are converted, through a transformation matrix $\mathbf{P}$, into L ($L \leq M$) new orthogonal components $\hat{\mathbf{x}}_j$, with $j = 1, 2, \cdots, L$, of the transformed data matrix $\hat{\mathbf{X}} = (\hat{\mathbf{x}}_1, \hat{\mathbf{x}}_2, \cdots, \hat{\mathbf{x}}_L)$. The relation between the $N \times M$ original data matrix ($\mathbf{X}$) and the $N \times L$ transformed one ($\hat{\mathbf{X}}$) is defined by the following linear combination,

$$\hat{\mathbf{X}} = \mathbf{X}\mathbf{P} \tag{3}$$

with $\mathbf{P}$ being the $M \times L$ transformation matrix and N being the number data samples. The columns of the transformed matrix ($\hat{\mathbf{X}}$) are sorted according to their contribution to maximize the covariance between the new components and the output vector $\mathbf{y}$. By using the iterative SIMPLS algorithm described in [22] we can obtain the transformation matrix $\mathbf{P}$. As long as the signal statistics do not change significantly, the transformation matrix $\mathbf{P}$ 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 $\mathbf{w}_{\text{PA}}$. Following the notation in Fig. 1, the estimated output vector $\hat{\mathbf{y}}$ of a PA behavioral model can be defined as

$$\hat{\mathbf{y}} = \mathbf{X}\mathbf{w}_{\text{PA}} \tag{4}$$

with $\mathbf{w}_{\text{PA}}$ being the vector of estimated coefficients and $\mathbf{X}$ is the data matrix containing the basis functions of the PA model. The coefficients are estimated as

$$\mathbf{w}_{\text{PA}} = (\mathbf{X}^H \mathbf{X})^{-1} \mathbf{X}^H \mathbf{y} \tag{5}$$

where $\mathbf{y} = (y[0], y[1], \cdots, y[N-1])^T$ is the $N \times 1$ vector of measured PA output data. The estimation of the coefficients $\mathbf{w}_{\text{DPD}}$ of the DPD function is performed iteratively in a similar way (see Fig. 1) with $\mathbf{U}$ 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 and the application of some regularization techniques will be necessary. 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 $\hat{\mathbf{X}}$ is composed by L ($L \leq M$) orthogonal components, which significantly simplifies the parameter extraction. Thanks to the orthogonality of the components of $\hat{\mathbf{X}}$, the matrix inversion of the correlation matrix in (5) can be simplified as follows,

$$\left(\hat{\mathbf{X}}^H \hat{\mathbf{X}} \right)^{-1} = \left(\sigma_1^{-1}, \sigma_2^{-1}, \cdots, \sigma_L^{-1} \right) \mathbf{I} \tag{6}$$

where σ_j, with $j = 1, 2, \cdots, L$, is the ℓ_2-norm squared of the new basis function $\hat{\mathbf{x}}_j = (\hat{x_j}[0], \hat{x_j}[1], \cdots, \hat{x_j}[N-1])^T$ of the new transformed matrix $\hat{\mathbf{X}} = (\hat{\mathbf{x}}_1, \hat{\mathbf{x}}_2, \cdots, \hat{\mathbf{x}}_L)$ and $\mathbf{I}$ is the

identity matrix. Therefore, the computation of each one of the new (transformed) coefficients $\hat{w}_j$, with $j = 1, 2, \cdots, L$, can be calculated independently as follows

$$\hat{w}_j = \sigma_j^{-1} \hat{\mathbf{x}}_j^H \mathbf{y} \qquad (7)$$

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

$$\mathbf{w}_{\text{PA}} = \mathbf{P} \hat{\mathbf{w}}_{\text{PA}} \qquad (8)$$

with $\mathbf{P}$ 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 (ii) 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 LM3290-91-1EVM 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):

TABLE I
COMPARISON OF DIFFERENT OMP COEFFICIENT SELECTION METHODS
FOR 3D-DML DPD

Method	Pout [dBm]	η [%]	NMSE [dB]	ACPR [dB]	Num. coeff.
(a) No OMP	23.1	19.0	B1: -36.5 B2: -37.7	B1: -45.6 B2: -46.0	B1: 85 B2: 153
(b) OMP-col	22.8	18.2	B1: -36.3 B2: -37.5	B1: -45.1 B2: -45.3	B1: 92 B2: 92
(c) OMP-LUT	23.0	18.7	B1: -36.5 B2: -37.1	B1: -45.1 B2: -45.3	B1: 62 B2: 73

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 three 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
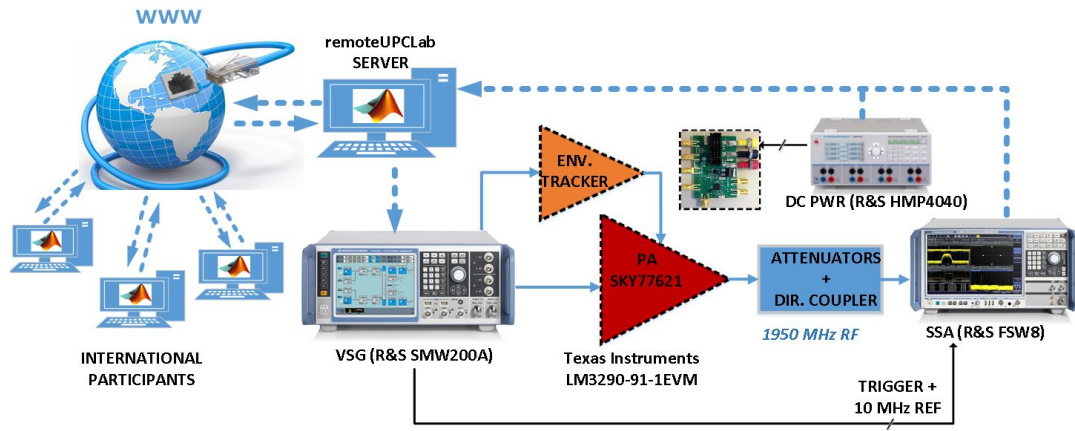
Fig. 2. Block diagram of the remoteUPCLab [23].

TABLE II
MOORE-PENROSE INVERSE VS. MATLAB'S BACKSLASH OPERATOR FOR
THE PA BEHAVIORAL MODELING AFTER APPLYING DIFFERENT
COEFFICIENT SELECTION METHODS

Method	Sig.	# of coef.	NMSE [dB]		ACEPR [dB]	
			MP–LS	\	MP–LS	\
(a)	B1	85	NaN	-39.8	NaN	-43.8
No OMP	B2	153	NaN	-46.0	NaN	-51.1
(b)	B1	92	-39.4	-39.4	-43.4	-43.4
OMP-col	B2	92	-45.9	-45.9	-50.7	-50.7
(c)	B1	62	NaN	-40.0	NaN	-44.0
OMP-LUT	B2	73	NaN	-45.6	NaN	-50.3

Fig. 3. NMSE and ACEPR vs. number of coefficients considering No-OMP selection in the forward path, *a)* for Band 1 signal and *b)* for Band 2 signal.

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
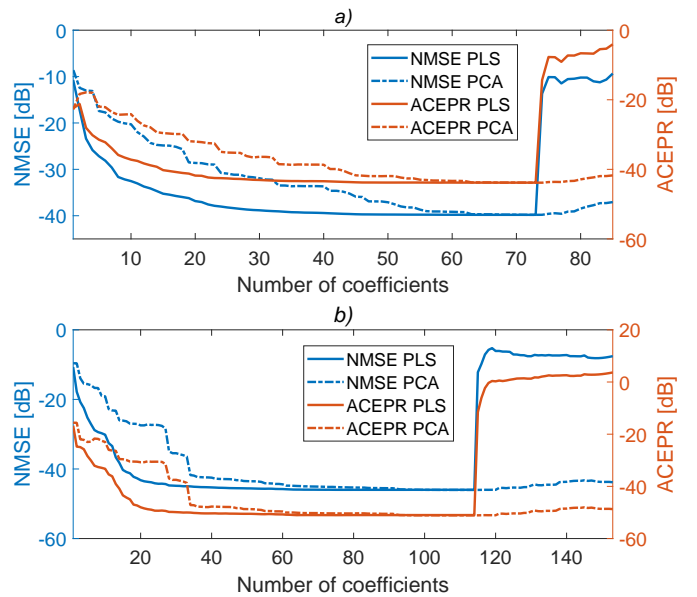
PCA, takes also into account the information of the output signal for creating the transformation matrix.

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
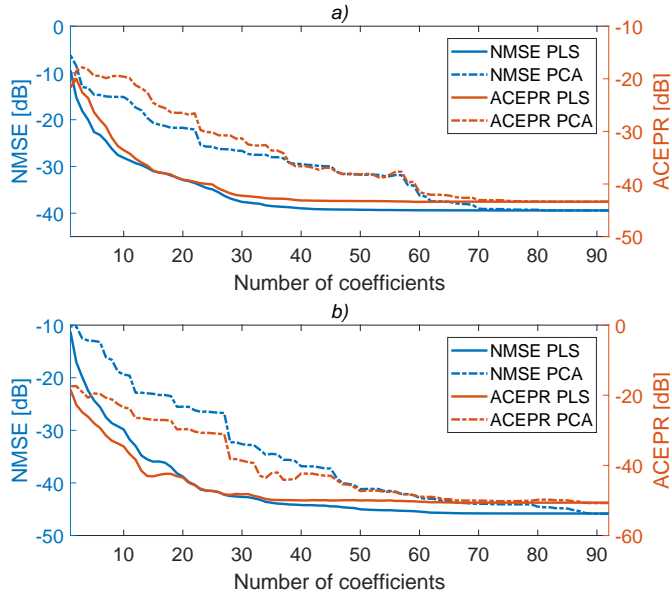
Fig. 4. NMSE and ACEPR vs. number of coefficients considering OMP-col selection in the forward path, *a)* for Band 1 signal and *b)* for Band 2 signal.
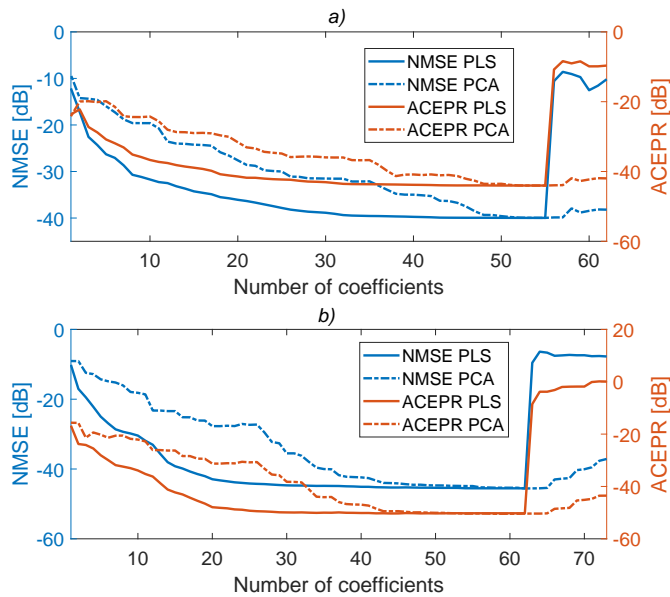

Fig. 5. NMSE and ACEPR vs. number of coefficients considering OMP-LUT selection in the forward path, *a)* for Band 1 signal and *b)* for Band 2 signal.

number of components, while only degradation is appreciated, as expected, when significantly decreasing the number of parameters.

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.
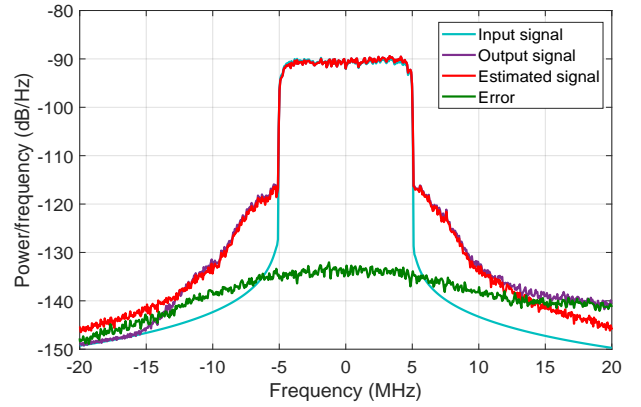

Fig. 6. Spectra of the input, measured output, estimated output and residual error of Band 1 signal when applying 'OMP-LUT and PLS reduction'.
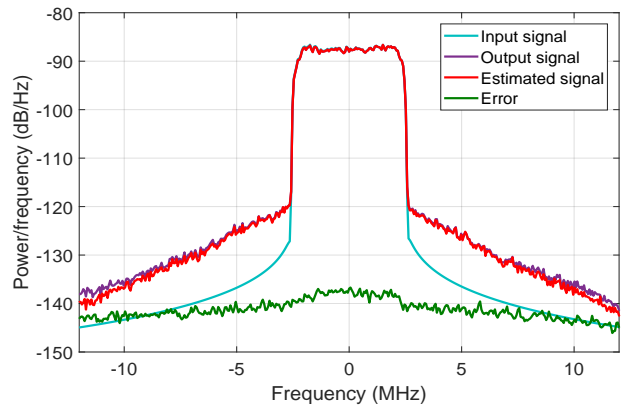

Fig. 7. Spectra of the input, measured output, estimated output and residual error of Band 2 signal when applying 'OMP-LUT and PLS reduction'.

Fig. 6 (for Band 1) and Fig. 7 (for Band 2) show the spectra of the estimated outputs considering a 3D-DML behavioral model after applying OMP-LUT selection (i.e., 62 coeff. Band 1 and 73 coeff. Band 2) and reduced PLS coefficient estimation (i.e., 40 coeff. Band 1 and 48 coeff. Band 2). Finally, applying the aforementioned combination (i.e., OMP-LUT selection in the forward path and PLS reduction estimation in the feedback identification path) we can significantly reduce the complexity of the 3D-DML DPD while still meeting the specific linearity requirements as shown in Fig. 8. Further details on the linearization performance of the 3D-DML DPD can be found in [10].

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).

TABLE III
PLS-BASED BEHAVIORAL MODELING IDENTIFICATION AFTER OMP-LUT COEFFICIENT REDUCTION

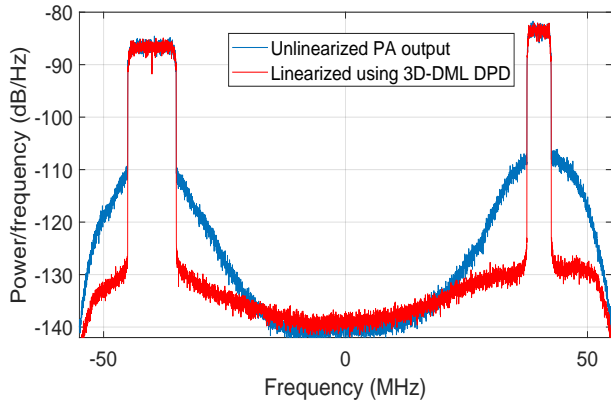| Signal	Number of coefficients			NMSE [dB]			ACEPR [dB]		
	backslash "\"	PLS reduction	↓ %	backslash "\"	PLS reduction	↓ %	backslash "\"	PLS reduction	↓ %
Band 1	62	40	35.5	-40.0	-39.8	0.5	-44.0	-43.8	0.5
Band 2	73	48	34.2	-45.6	-45.4	0.4	-50.3	-50.3	0.0

Fig. 8. Unlinearized and linearized (using the 3D-DML DPD and the OMP-LUT configuration in Table I) spectra of a DB signal.

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.

ACKNOWLEDGMENT

REFERENCES

[1] Z. Wang, *Envelope Tracking Power Amplifiers for Wireless Communications.* Norwood, MA, USA: Artech House, Inc., 2014.

[2] Y. Liu, C.-S. Yoo, J. Fairbanks, J. Yan, D. Kimball, and P. Asbeck, "A 53% PAE envelope tracking GaN power amplifier for 20MHz bandwidth LTE signals at 880MHz," in *2016 IEEE Topical Conference on Power Amplifiers for Wireless and Radio Applications (PAWR).* IEEE, Jan. 2016.

[3] C. Kim, C.-S. Chae, Y.-S. Yuk, C. M. Thomas, Y.-G. Kim, J.-K. Kwon, S. Ha, G. Cauwenberghs, and G.-H. Cho, "A 500-MHz bandwidth 7.5-mVpp ripple power-amplifier supply modulator for RF polar transmitters," *IEEE Journal of Solid-State Circuits*, pp. 1–13, 2018.

[4] G. Montoro, P. Gilabert, E. Bertran, and J. Berenguer, "A method for real-time generation of slew-rate limited envelopes in envelope tracking transmitters," in *RF Front-ends for Software Defined and Cognitive Radio Solutions (IMWS), 2010 IEEE International Microwave Workshop Series on*, 2010, pp. 1–4.

[5] P. L. Gilabert, G. Montoro, D. Lopez, and J. A. Garcia, "3D Digital predistortion for dual-band envelope tracking power amplifiers," in *Microwave Conference Proceedings (APMC), 2013 Asia-Pacific*, 2013, pp. 734–736.

[6] Y. Lin, H. Jang, C. Quindroit, N. Naraharisetti, and P. Roblin, "New supply modulation optimization methodology for concurrent dual band envelope tracking power amplifier," in *Proc. IEEE Wireless and Microwave Technology Conference (WAMICON 2014)*, Jun. 2014, pp. 1–4.

[7] P. L. Gilabert and G. Montoro, "3-D distributed memory polynomial behavioral model for concurrent dual-band envelope tracking power amplifier linearization," *IEEE Transactions on Microwave Theory and Techniques*, vol. 63, no. 2, pp. 638–648, Feb. 2015.

[8] H. Sarbishaei, B. Fehri, Y. Hu, and S. Boumaiza, "Dual-band Volterra series digital pre-distortion for envelope tracking power amplifiers," *Microwave and Wireless Components Letters, IEEE*, vol. 24, no. 6, pp. 430–432, Jun. 2014.

[9] A. Kwan, M. Younes, S. Zhang, W. Chen, R. Darraji, M. Helaoui, and F. M. Ghannouchi, "Dual-band predistortion linearization of an envelope modulated power amplifier operated in concurrent multi-standard mode," in *Microwave Symposium Digest (IMS), 2013 IEEE MTT-S International*, Jun. 2014.

[10] Q. A. Pham, D. López-Bueno, T. Wang, G. Montoro, and P. L. Gilabert, "Multi-dimensional LUT-based digital predistorter for concurrent dual-band envelope tracking power amplifier linearization," in *Proc. IEEE Topical Conference on RF/Microwave Power Amplifiers for Radio and Wireless Applications (PAWR2018)*, Jan. 2018, pp. 1–4.

[11] A. Molina, K. Rajamani, and K. Azadet, "Concurrent dual-band digital predistortion using 2-D lookup tables with bilinear interpolation and extrapolation: Direct least squares coefficient adaptation," *IEEE Transactions on Microwave Theory and Techniques*, vol. 65, no. 4, pp. 1381–1393, Apr. 2017.

[12] J. Reina-Tosina, M. Allegue-Martinez, C. Crespo-Cadenas, C. Yu, and S. Cruces, "Behavioral modeling and predistortion of power amplifiers under sparsity hypothesis," *IEEE Transactions on Microwave Theory and Techniques*, vol. 63, no. 2, pp. 745–753, Feb. 2015.

[13] L. Guan and A. Zhu, "Optimized low-complexity implementation of least squares based model extraction for digital predistortion of RF power amplifiers," *Microwave Theory and Techniques, IEEE Transactions on*, vol. 60, no. 3, pp. 594–603, 2012.

[14] Q. Zhang and Z. Zeng, "A new adaptive algorithm for digital predistortion using LS with singular value decomposition," in *International Conference on Information Science and Technology Application (ICISTA-13)*, 2013, pp. 169–172.

[15] E. Abd-Elrady, "A recursive prediction error algorithm for digital predistortion of FIR Wiener systems," in *Communication Systems, Networks and Digital Signal Processing, 2008. CNSDSP 2008. 6th International Symposium on*, Jul. 2008, pp. 698–701.

[16] R. Braithwaite, "Wide bandwidth adaptive digital predistortion of power amplifiers using reduced order memory correction," in *Microwave Symposium Digest, 2008 IEEE MTT-S International*, 2008, pp. 1517–1520.

[17] M. Rawat, F. Ghannouchi, and K. Rawat, "Three-layered biased memory polynomial for dynamic modeling and predistortion of transmitters with memory," *Circuits and Systems I: Regular Papers, IEEE Transactions on*, vol. 60, no. 3, pp. 768–777, Mar. 2013.

[18] I. Jolliffe, *Principal Component Analysis.* Springer-Verlag, 2002.

[19] P. L. Gilabert, G. Montoro, D. Lopez, N. Bartzoudis, E. Bertran, M. Payaro, and A. Hourtane, "Order reduction of wideband digital predistorters using principal component analysis," in *Microwave Symposium Digest (IMS), 2013 IEEE MTT-S International*, 2013, pp. 1–4.

[20] R. Rosipal and N. Krämer, "Overview and recent advances in partial least squares," in *Subspace, Latent Structure and Feature Selection.* Springer Berlin Heidelberg, 2006, pp. 34–51.

[21] S. Haykin, *Neural Networks and Learning Machines*, ser. Neural networks and learning machines. Prentice Hall, 2009.

[22] S. de Jong, "SIMPLS: An alternative approach to partial least squares regression," *Chemometrics and Intelligent Laboratory Systems*, vol. 18, no. 3, pp. 251–263, Mar. 1993.

[23] [Online]. Available: http://dpdcompetition.com/sdc/

Quynh Anh Pham (S'18) received the M.Sc. degree in Computer Science and Engineering from the Soongsil University, Seoul, South Korea, in 2015. Since 2017, she has been with the department of Signal Theory and Communications (TSC) at Universitat Politcnica de Catalunya (UPC), Barcelona, Spain where she is currently pursuing the Ph.D. degree. Her research interests include wireless communications, nonlinear behavioral modeling and linearization techniques for high-efficiency transmitters in wireless communication systems.

Pere L. Gilabert (M'09-SM'13) received his M.Sc. degree in Telecommunication Engineering from the Universitat Politècnica de Catalunya (UPC) in 2002, and he developed his Master Thesis at the University of Rome La Sapienza with an Erasmus exchange grant. He joined the department of Signal Theory and Communications (TSC) in 2003 and received his Ph.D., awarded with the Extraordinary Doctoral Prize, from the UPC in 2008. He is an Associate Professor at the Castelldefels School of Telecommunications and Aerospace Engineering (EETAC-UPC). His research activity is in the field of linearization techniques and digital signal processing solutions for highly efficient transmitter architectures.

David López–Bueno (M'13) received his M.Sc. degree in Telecommunication Engineering from the Universitat Politècnica de Catalunya (UPC) in 2005. Starting 2003, he worked for four years as RF module & MMIC Design Engineer in space companies. By late 2006, he joined the CTTC as Research Engineer and since then he has participated in a number of research projects dealing with RF transceivers, 4G/5G MIMO OFDM-based lab demonstrators, and assessing the risk of interference between heterogeneous systems. Since 2013, he is also working in projects in the field of wideband PA digital linearization for radio equipment which has led him to pursue a Phd on this topic at UPC–Barcelona Tech.

Teng Wang received the Bachelors degree in Jet Propulsion from Beijing University of Aeronautics and Astronautics ,Beijing, China, in 2013, the Masters degree in Aerospace Science and Technology from Universitat Politcnica de Catalunya (UPC), Barcelona, Spain, in 2015, and is currently working toward the Ph.D. degree at Universitat Politcnica de Catalunya (UPC), Barcelona, Spain. From 2014 to 2018, he was with the Department of Signal Theory and Communications (TSC), where his research focused on digital predistortion and PA linearization. He is also currently working with Cielo Co., Ltd in Beijing, China, where his research is focused on high efficiency power amplifier and its industrial application. His research interests include power amplifier modeling, digital predistortion, highly efficient power amplifier and business management.

Gabriel Montoro (M'09) received the M.Sc. degree in telecommunication engineering and the Ph.D. degree from the Universitat Politcnica de Catalunya (UPC), Barcelona, Spain, in 1990 and 1996, respectively. He joined the Department of Signal Theory and Communications (TSC) in 1991, where he is currently an Associate Professor. His first research works were done on the area of adaptive control, and now his main research interest is in the use of signal processing strategies for power efficiency improvement in communications systems.