Determining a Pruned 2-D Digital Predistortion Model Structure for Power Amplifiers Linearization

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***Abstract*—Two-dimensional digital predistortion (2-D DPD) is one of the most commonly used approach to linearize the concurrent dual-band radio frequency (RF) power amplifiers (PA). In this paper, we propose to determine an optimal structure of a dual-band DPD model using an optimization-heuristic-based method. A new form for 2-D DPD is proposed for lower complexity. We propose a search criterion based on generalized information criterion which represents the trade-off between the DPD linearization performance in two bands and its model complexity. A comparison against a compressed-sensing-based method is also made. The effectiveness of the proposed method is validated with two 20 MHz long-term-evolution (LTE) signals on two carriers with 100 MHz frequency separation.**

***Index Terms*—Digital predistortion, information criterion, non-linear distortion, opitmization, RF power amplifiers**

I. Introduction

Multi-band power amplifiers (PA) are designed for the compatibility of different standards in modern wireless communication systems [1]. The conventional single-band digital predistortion (DPD) becomes difficult for the linearization since the feedback bandwidth has been largely increased if we regard the dual-band signal as a single broadband signal. A 2-D memory polynomial (MP) model DPD is proposed in [2] by processing the signals in different bands separately.

Determining the model structure according to a trade-off between the model accuracy and complexity is an important step before estimating the model coefficients. Some optimization heuristic (OH) methods have been proposed to address this problem [3] [4]. In [3], an algorithm based on hill-climbing heuristic has been developed for sizing single-band generalized memory polynomial (GMP) model.

These methods determine the optimal full models with minimal nonlinearity orders and memory depths for an acceptable linearization performance. The sparse models are considered in [5] for the case of 2-stage cascade MP models. Determining a sparse model structure is equivalent to pruning a complete model whose nonlinearity order and memory depth are infinite. A compressed sensing (CS) method under sparsity hypothesis to select only important model kernels has been proposed for the model pruning in [6]. This pruning technique is applied for the case of 2D-MP model in [7].

In this paper, we use an OH-based method to determine an optimal pruned structure of the 2-D MP model. Then we propose a new form for the 2-D MP model for further pruning with the OH-based method. Besides a comparison against the CS-based pruning technique is given. In the simulations, the stimulus is composed of two 20 MHz long term evolution (LTE) signals on different bands.

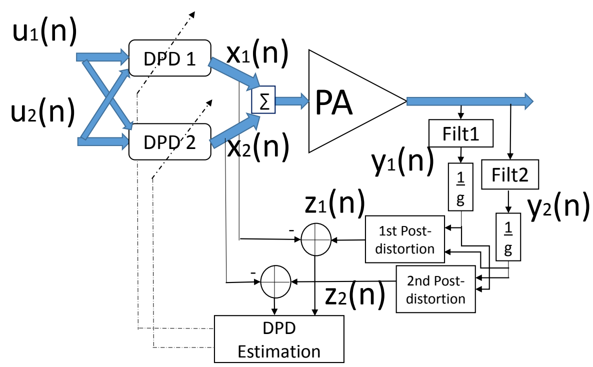

Fig. 1. Dual-band system architecture

This paper is organized as follows. Section II presents the structure of the DPD. The OH-based method is proposed to size the 2-D DPD model structure and compared with CS-based method in Section III. The simulation results are given in Section IV. Finally, the conclusion is given in Section V.

II. DPD structure

A. Model Structure

The dual-band system is depicted in Fig 1. The signals of lower and upper band are denoted by $u_1(n)$ and $u_2(n)$ respectively. The feedback signals $y_i(n)$ of the i-th band can be also extracted from the PA output with filters according to their carrier frequencies, where $i = 1, 2$. In this paper, we use a 2-D MP model as the DPD. The DPD model for the i-th band can be written as

$$\begin{aligned} x_i(n) = &\sum_{k=0}^{\mathcal{K}-1} \sum_{j=0}^{k} \sum_{l=0}^{\mathcal{L}-1} \gamma_{kjl}^{(i)} u_i(n-l) \\ &\times |u_i(n-l)|^{k-j} |u_{3-i}(n-l)|^j \\ =&f_i(u_1(n), u_2(n)) \end{aligned} \tag{1}$$

where k is the index for nonlinearity, l is the indices for memory, and γ_{kjl} is the complex coefficient.

B. Model Identification

In this structure, a post-distortion is identified and then applied upstream of the PA as the DPD. The i-th band model coefficients are estimated using the PA input signal $x_i(n)$ and the PA output signal $y_i(n)$ normalized by its gain g. Denoting the normalized PA output by $\tilde{y}$, we express the post-distortion output of the i-th band in function of PA output signals on both two band:

$$z_i(n) = f_i(\tilde{y}_1(n), \tilde{y}_2(n)). \tag{2}$$

As different possible choices for g achieve about the same PA efficiency [8], we choose the small signal gain in this paper.

The identification is based on indirect learning architecture (ILA) [3] so that we can take the average of dual band normalized mean square error (NMSE) between $x_i(n)$ and $z_i(n)$ to represent the modeling accuracy:

$$Y = 10log_{10}\left[\frac{\mathrm{NMSE}_1 + \mathrm{NMSE}_2}{2}\right] \tag{3}$$

where for $i = 1, 2$

$$\mathrm{NMSE}_i = \frac{\sum_{n=1}^{N} |x_i(n) - z_i(n)|^2}{\sum_{n=1}^{N} |x_i(n)|^2}. \tag{4}$$

In the case of determining the DPD model structure in this paper, $x_i(n)$=$u_i(n)$ for i=1,2.

The model coefficients can be estimated by solving a linear problem. For each band, we can express the post-distortion using matrix notation for a block of N samples:

$$\boldsymbol{z_i} = \boldsymbol{\Psi}_i \boldsymbol{\gamma_i} \tag{5}$$

where $\boldsymbol{z_i}$= $[z_i(1), \ldots, z_i(N)]^T$, $\boldsymbol{\Psi}_i$ is $N \times R$ matrix containing basis functions and R is the total number of model coefficients. The LS estimation of $\boldsymbol{\gamma_i}$ is found by solving

$$[\boldsymbol{\Psi}_i^H \boldsymbol{\Psi}_i]\hat{\boldsymbol{\gamma}}_{\boldsymbol{i}} = \boldsymbol{\Psi}_i^H \boldsymbol{x_i} \tag{6}$$

which minimizes the cost function (4).

III. Model complexity reduction methods

A. Optimization-heuristic-based method

Hill-climbing heuristic is an optimization algorithm with a rapid progress converging to a local optimum. It has been confirmed robust for DPD model structure optimization problem since its local optima are very close to or even the same as the global optimum [3].

We propose to use the algorithm based on hill-climbing method for 2D-MP model structure determination. At the 1st iteration we choose a starting point $M_{0(1)}$ and calculate its merit value $J(M_{0(1)})$ as well as its neighbors. If the best neighbor element $M_{s(1)}$ is better than $M_{0(1)}$, we take it as the starting point of the next iteration $M_{0(2)}$. Otherwise we take the $M_{0(1)}$ as the final solution and the procedure ends.

For the full model with nonlinearity orders $\boldsymbol{k} = [0 : \mathcal{K} - 1]$ and memory depth $\boldsymbol{l} = [0 : \mathcal{L} - 1]$, the number of coefficients equals to $\frac{1}{2}\mathcal{K}(\mathcal{K}+1)\mathcal{L}$. Pruning the model, especially pruning the nonlinearity arrays $\boldsymbol{k}$, can sharply decrease the model complexity.

The sparsity can be denoted by S that we select $S - 1$ elements from $\mathcal{K} - 1$ element array $[1 : \mathcal{K} - 1]$ (element 0 is always in the array $\boldsymbol{k}$ and $\boldsymbol{l}$). All possible combinations of the elements of vector $[1 : \mathcal{K} - 1]$ taken $S - 1$ at a time can be listed in increasing order. Then each combination are indicated by its index I and S. Since the parameters k and l are independent of each other, we treat them in the same way.

Noticing the dynamic range of parameter j in (1) varies according to k, it is very difficult to list the sparse arrays in the same way. Thus we propose to rewrite (1) as following:

$$\begin{aligned} x_i(n) = &\sum_{m=0}^{\mathcal{K}-1} \sum_{\substack{j=0 \\ m+j \leqslant \mathcal{K}-1}}^{\mathcal{K}-1} \sum_{l=0}^{\mathcal{L}-1} \gamma_{kjl}^{(i)} u_i(n-l) \\ &\times |u_i(n-l)|^m |u_{3-i}(n-l)|^j, \end{aligned} \tag{7}$$

The structure of a 2-D MP model can then be represented by 6 parameters: (S_m, I_m; S_j, I_j; S_l, I_l). Thus we can construct a 6-D discrete space where each point represents a model structure. Two constraints for M_d to be a neighbor of M_i:

1) The parameters of M_d can be represented by ($S_m^{(i)} \pm 1$, $I_m^{(i)} \pm 1$; $S_j^{(i)} \pm 1$, $I_j^{(i)} \pm 1$; $S_l^{(i)} \pm 1$, $I_l^{(i)} \pm 1$).
2) The variation of number of coefficients $|R_d - R_i| \leqslant d$, where d is a given threshold.

B. Compressed-sensing-based method

We take the orthogonal matching pursuit (OMP) algorithm as a reference in this paper to solve this CS problem. First, with the PA output signal in the i-th band, we construct the basis matrix $\boldsymbol{\Psi_i}$ of the complete model M_{comp} with $\mathcal{K}$ and $\mathcal{L}$ as the maximal nonlinearity order and memory depth respectively. The model $M_{(q)}$ contains q basis functions. At the beginning, $M_{(0)}$ is an empty set. We select the most important basis function from $\boldsymbol{\Psi_i}$ and add it to our model $M_{(q)}$ at each iteration. Thus q represents also the number of iterations. The importance of the basis functions are determined by the product

$$I(c) = \frac{|\boldsymbol{\Psi}_c^H \boldsymbol{r}_{(q-1)}|}{||\boldsymbol{\Psi}_c||} \tag{8}$$

where $\boldsymbol{\Psi}_c$ is the column of the c-th basis function, $\boldsymbol{r}_{(q-1)}$ is the residual at the $(q-1)$-th iteration. The residual is initialized as $\boldsymbol{r}_{(0)} = \boldsymbol{z_i}$ and it is updated at each iteration with the estimated model output:

$$\boldsymbol{r}_{(q)} = \boldsymbol{r}_{(q-1)} - \boldsymbol{\Psi_i}\hat{\boldsymbol{\gamma}}^{\boldsymbol{i}} \tag{9}$$

where the coefficients $\hat{\boldsymbol{\gamma}}^{\boldsymbol{i}}$ are estimated using (6). The algorithm ends when a given stall condition is reached.

C. Merit function

In order to find the optimal model respecting the trade-off between modeling accuracy and model complexity, we

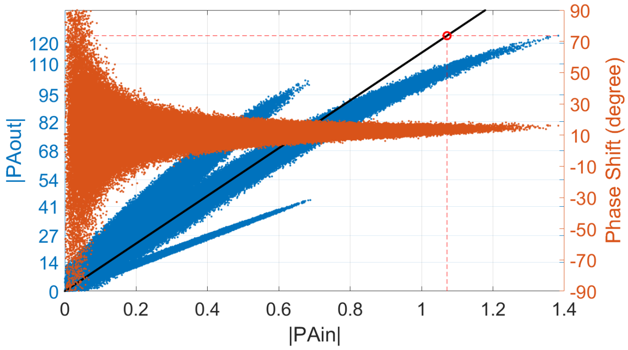

Fig. 2. AM/AM & AM/PM curve of Wiener model PA for dual-band LTE

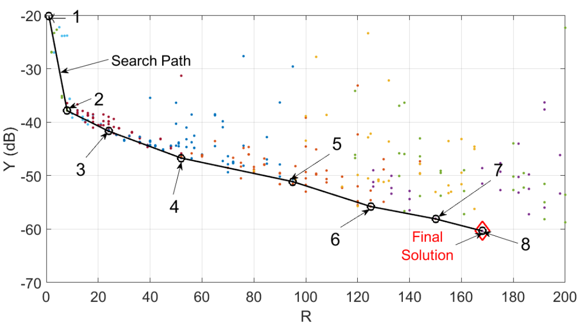

Fig. 3. Search path of OH-based method for 2D-MP model structure

compute merit values according to the generalized information criterion (GIC) [9]. The GIC can be written as

$$GIC = -2 \ln p(\boldsymbol{x}, \hat{\boldsymbol{\gamma}}^{(R)}) + (1+\rho)R \tag{10}$$

where $p(\boldsymbol{x}, \hat{\boldsymbol{\gamma}}^{(R)})$ is the likelihood function of the data vector $\boldsymbol{x}$ which depends on the $1 \times R$ parameter vector $\hat{\boldsymbol{\gamma}}^{(R)}$. In case of 2D-MP model, we have in the i-th band

$$\begin{aligned} -2 \ln p(\boldsymbol{x}_i, \hat{\boldsymbol{\gamma}_i}^{(R)}) =& N \ln(\frac{1}{N} ||x_i(n) - z_i(n)||^2) + cst \\ =& \frac{N \ln 10}{10} \text{NMSE}_i + cst \end{aligned} \tag{11}$$

where cst is a constant. Considering the performances in both two bands, we propose the merit function as following:

$$J = Y + \frac{10 \cdot (1+\rho)}{N \ln 10} R = Y + \mu R. \tag{12}$$

Since the importance of basis function can be computed for the signals of only one band at a time, the CS-based method determines the model structure separately for the two bands and thus they can be different. We take $R = \frac{1}{2}(R_1 + R_2)$ in (12) for the merit value of the CS-based method solution.

IV. Simulation Results

We create a dual-band signal with 100 MHz frequency separation as the stimulus. The signal in each band is a 20 MHz LTE signal. The signal is fed to a Wiener model PA. The

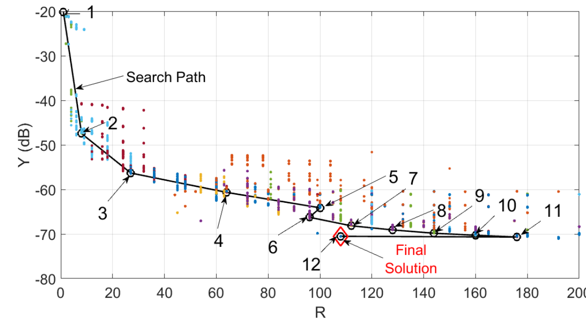

Fig. 4. Search path of New OH-based method for 2D-MP model structure

TABLE I
Performances of Different Methods

	Y	R	J	ACPR (dB) Band 1/2			
	(dB)	(Band 1/2)		1.L	1.U	2.L	2.U
OH	-60.3	168/168	-57.0	-65.5	-65.4	-70.9	-69.4
NOH	-70.5	108/108	-68.4	-78.9	-82.3	-69.1	-64.8
N_{25}	-66.7	48/48	-65.8	-71.9	-74.5	-61.1	-55.3
CS1	-62.9	108/108	-60.7	-74.2	-76.1	-73.0	-68.7
CS2	-67.9	144/136	-65.1	-76.2	-79.2	-73.8	-72.1

N_{25}: NOH with d=25.

AM/AM & AM/PM (Amplitude Modulation/Amplitude Modulation & Amplitude Modulation/Phase Modulation) curves of the PA are illustrated in Fig 2.

In the following tests, we use the dataset with $N = 30000$ samples. Depending on the considered scenario as well as the value of N, we set $\mu = 0.02$ for the merit function which represents that we trade-off 1dB on NMSE with 50 coefficients. All tests are computed with Intel Core i7-7500U CPU @ 2.70GHz.

The simulation results of the OH-based method and the CS-based method are listed and compared in Table I. Firstly we apply the OH-based method on a 4D space composed of models (1), which is denoted by "OH". We set d=50 for the neighborhood constraint. Secondly, we apply the OH-based method on 6D space composed of 2-D MP models in new form (7), which is denoted by "NOH". The maximum orders are set $\mathcal{K}$=$\mathcal{L}$=15.

As the modeling accuracy is represented by the error between the post-distortion output $z_i(n)$ and the stimulus $u(n)$ as (4), the spectra of $z_1(n)$ and $z_2(n)$ given by different methods are depicted along with the spectrum of $u(n)$ in Fig 6 and Fig 7 respectively. The lower/upper adjacent channel power ratios (ACPR.L/U) of each band are also given in Table I.

1) Results of OH-based method: The search path of the proposed OH-based method is shown in Fig 3. The colorful points are tested models. The black circles represent solutions of each iteration (the number of the iteration is indicated beside), which trace the search path of the algorithm converging towards the red diamond. The final solution has R=168 coefficients and Y=-60.3 dB, $\boldsymbol{k}$=[0:4, 8], $\boldsymbol{l}$=[0:5, 8]. There are totally 323 models tested during 9.6 minutes.

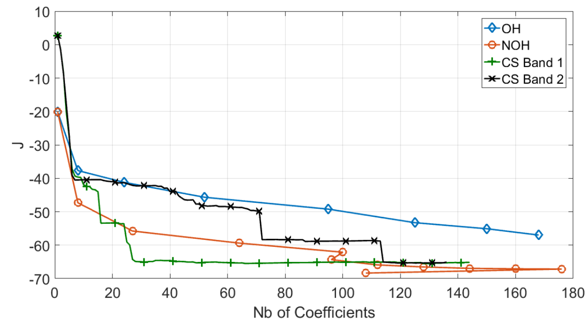

Fig. 5. Evolution of merit value for different methods

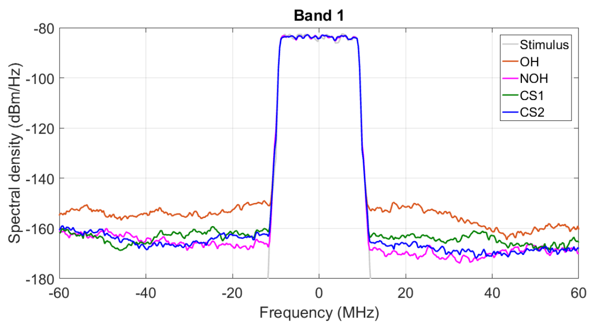

Fig. 6. Spectra of the post-distortion output in the 1st band

2) Results of new OH-based method (NOH): The search path of NOH is shown in Fig 4. The final solution has R=108 coefficients and Y=-70.5 dB, $\boldsymbol{m}$=[0:2], $\boldsymbol{j}$=[0:2], $\boldsymbol{l}$=[0:10, 12]. There are totally 2435 models tested during 90.9 minutes.

3) Results of new OH-based method (NOH) with d=25: Since NOH has 6-D search space, its number of tests is greater than that of OH. We test with d=25 for a search with similar execution time of OH for a comparison in Table I. The final solution has R=48 coefficients and Y=-66.7 dB, $\boldsymbol{m}$=[0:1], $\boldsymbol{j}$=[0:2], $\boldsymbol{l}$=[0:7]. We test 1345 models during 12.8 minutes.

4) Result of CS-based method: We set the orders of the complete model M_{comp} in CS method $\mathcal{K}$=$\mathcal{L}$=15 same as in OH and NOH. We test the algorithm with different stall conditions. In Table I and Fig 6-7, "CS1" ends when R=108, "CS2" ends when $J(M_{(q)})$ better than $0.9 \times J(M_{(q-1)})$ at the q-th iteration.The solution given by the CS1 reaches an NMSE value Y=-62.9 dB. The execution time is 47.1 minutes. The solution given by the CS2 reaches an NMSE value Y=-67.9 dB with 144 coefficients for the 1st band and 136 for the 2nd band. The execution time is 54.6 minutes.

The evolution of merit values in function of number of coefficients are illustrated in Fig 5. The proposed NOH methods can reach the better merit value than OH and CS methods.

Compared with the conventional OH method, NOH improves linearization performance about 10 dB with less coefficients. Comparing Fig. 3 and Fig. 4, we can see that the formula (7) allows NOH to test the models with NMSE lower than -60 dB and coefficients less than 100. The solution given by CS1 has the same number of coefficients with that of NOH

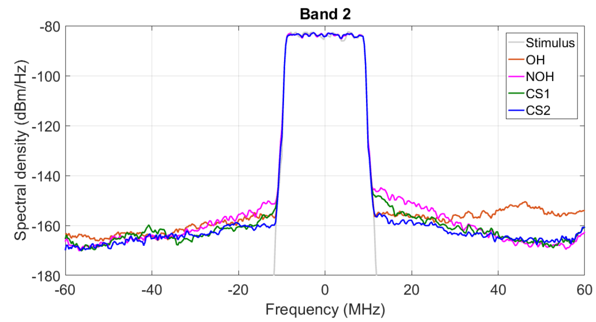

Fig. 7. Spectra of the post-distortion output in the 2nd band

but its linearization performance is very weak. The solution given by CS2 achieves similar linearization performance with that of NOH but with much more coefficients.

V. Conclusion

In this paper, we extend the search algorithm proposed in [5] for a 2-D MP model. We propose a new form of 2-D MP model which leads to a model with much less complexity. A search criterion based on GIC is used. A comparison against the CS-based pruning technique validates the advantages of the proposed NOH method on solution model complexity.Future work includes studying the impact of d on the algorithm and determining the models in each band separately.

References

[1] W. Chen, S. A. Bassam, X. Li, Y. Liu, K. Rawat, M. Helaoui, F. M. Ghannouchi, and Z. Feng, "Design and linearization of concurrent dual-band doherty power amplifier with frequency-dependent power ranges," *IEEE Trans. Microw. Theory Tech.*, vol. 59, no. 10, pp. 2537–2546, Oct 2011.

[2] S. Bassam, M. Helaoui, and F. Ghannouchi, "2-d digital predistortion (2-d-dpd) architecture for concurrent dual-band transmitters," *IEEE Trans. Microw. Theory Techn.*, vol. 59, no. 10, pp. 2547 –2553, oct. 2011.

[3] S. Wang, M. Abi Hussein, O. Venard, and G. Baudoin, "A novel algorithm for determining the structure of digital predistortion models," *IEEE Trans. Veh. Technol*, vol. 67, no. 8, pp. 7326–7340, Aug 2018.

[4] A. Abdelhafiz, L. Behjat, and F. M. Ghannouchi, "Generalized memory polynomial model dimension selection using particle swarm optimization," *IEEE Microw. Wireless Compon. Lett.*, vol. 28, no. 2, pp. 96–98, Feb 2018.

[5] S. Wang, M. Abi Hussein, O. Venard, and G. Baudoin, "Optimal sizing of two-stage cascaded sparse memory polynomial model for high power amplifiers linearization," *IEEE Trans. Microw. Theory Tech.*, vol. 66, no. 9, pp. 3958–3965, Sept 2018.

[6] J. Reina-Tosina, M. Allegue-MartÃnez, C. Crespo-Cadenas, C. Yu, and S. Cruces, "Behavioral modeling and predistortion of power amplifiers under sparsity hypothesis," *IEEE Trans. Microw. Theory Tech.*, vol. 63, no. 2, pp. 745–753, Feb 2015.

[7] S. Wu, J. Zhai, Z. Yu, and N. Zhang, "A compressed sensing method for pruning concurrent dual-band power amplifier models," in *2018 IEEE MTT-S International Wireless Symposium (IWS)*, May 2018, pp. 1–3.

[8] S. Wang, M. Abi Hussein, O. Venard, and G. Baudoin, "Impact of the normalization gain of digital predistortion on linearization performance and power added efficiency of the linearized power amplifier," in *2017 12th European Microwave Integrated Circuits Conference (EuMIC)*, Oct 2017, pp. 310–313.

[9] P. Stoica and Y. Selen, "Model-order selection: a review of information criterion rules," *IEEE Signal Process. Mag.*, vol. 21, no. 4, pp. 36–47, July 2004.