A High-performance Complexity Reduced Behavioral Model and Digital Predistorter for MIMO Transmitters with Crosstalk

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Abstract— In this paper, an augmented crossover memory polynomial model (A-COMPM) to be used for characterizing and linearizing multiple-input multiple-output (MIMO) transmitters in the presence of linear and nonlinear crosstalk is proposed and developed. By more accurately incorporating the effect of crosstalk, the proposed model significantly improves upon the performance of the crossover memory polynomial model (CO-MPM) and performs comparably to the 2x2 parallel Hammerstein (2x2 PH) model, while requiring the same number of coefficients as CO-MPM and a lower number of coefficients than the 2x2 PH. The model was tested for forward modeling and digital predistortion (DPD) applications in the presence of both linear and nonlinear crosstalk, and it was found through experimental results that the model outperforms the CO-MPM and 2x2 PH DPDs, at a lower number of coefficients compared to either model. Furthermore, the issue of numerical stability of the DPD extraction and implementation procedures is also addressed in the paper.

Index Terms—Behavioral modeling, condition number, crossover memory polynomial model, crosstalk, digital predistortion, fifth-generation networks, model complexity, multiple-input multiple-output (MIMO) transmitters, power amplifier nonlinearities.

I. INTRODUCTION

To accommodate for the increasing demand by users for faster data rates delivered at a higher quality of service, proposals for fifth-generation (5G) wireless communication standards utilizing large-scale multiple-input multiple-output (MIMO) architectures (also known as Massive MIMO) have begun to surface [1]. One of the main features of 5G is the use of large-scale MIMO systems with up to 100x100 MIMO systems being proposed [2]-[4]. The use of this technology enabled 5G to achieve data rates up to 7.5 Gb/s as demonstrated by Samsung recently [4]. However, the high level of integration in Massive MIMO results in the presence of strong leakage (or crosstalk) between the transmitter (TX) paths, which leads to the generation of more nonlinearities in the transmitters used [5]. This issue is further exacerbated by the use of envelope-varying signals with high peak-to-average power ratios (PAPRs) and wide signaling bandwidths, which results in the presence of even stronger nonlinearities in the TX hardware, thus degrading the energy efficiency and quality of service, therefore requiring the use of compensation methods [6]-[9]. In the literature, the digital predistortion (DPD) method has been widely adopted in the literature for the compensation of transmitter nonlinearities in various transmitter and carrier’s aggregated configurations [7]-[9].

In the context of MIMO, DPD has been used in the literature to successfully linearize 2xK (where K is the number of receive antennas) MIMO transmitters operating in the presence of weak or moderate crosstalk, or mitigate crosstalk through the use of equalization methods [9]-[18]. In [12], a DPD model approximating the output of a MIMO power amplifier (PA) as the sum of two nonlinear functions was proposed, known as the cross-over memory polynomial model (CO-MPM). It requires a low number of coefficients and performs well in the presence of moderate to weak crosstalk. However, its performance degrades when the crosstalk is strong due to the derivation approximation.

In [10] and [16], a variety of models utilizing multiple-input structures were studied and found to perform well for stronger levels of crosstalk, at the cost of needing a large number of coefficients. In this paper, the two-input 2x2 parallel Hammerstein (2x2 PH) model from [16] is used as a benchmark, as was done in [10].

The main contribution of this paper is to develop an efficient polynomial model which can linearize transmitters exhibiting strong crosstalk effects, known as the augmented crossover memory polynomial model (A-COMPM). This model accounts for crosstalk effects by incorporating the interaction between the signal paths and crosstalk more accurately than CO-MPM and 2x2 PH, while keeping the same number of basis functions in CO-MPM. As a result, the proposed model achieves a good balance between the accuracy of the two-input models in [10][16] and the low number of coefficients of the model in [12]. The theory for the model is established, and experimental results for the forward
modeling and linearization cases are provided.

The remainder of this paper is organized as follows: In Section II, the effect of crosstalk in MIMO transmitters is briefly reviewed, and two models available in the literature (namely CO-MPM and the 2x2 Parallel Hammerstein (2x2 PH models) are discussed. Section III covers the proposed model and a comparative study of the various models in terms of the number of coefficients required for each. Experimental measurements for behavioral modeling and linearization purposes are given in Section IV. In Section V, the work done is summarized, and conclusions are provided. Appendix A contains the details of the derivation of the proposed model.

II. LITERATURE REVIEW

A. Sources and Impact of Crosstalk in MIMO Transmitters

In addition to the usual TX imperfections such as gain- and phase-imbalance and mixer leakage, MIMO transmitters also suffer from crosstalk effects which degrade their performance. Crosstalk originates from the coupling between the different transmitter paths. As the integrated circuits (ICs) on which the MIMO transmitters are implemented tend to become smaller, the crosstalk grows stronger due to the fact that all branches utilize in most cases the same carrier frequency [18].

Broadly, crosstalk can be classified as linear and nonlinear crosstalk based on where it occurs in the TX [12]. Fig. 1. shows a typical 2xK MIMO transmitter suffering from both types of crosstalk. These two categories are defined below:

a. Linear crosstalk: This form of crosstalk occurs after the PA and before the antenna; which means that it does not pass through the nonlinear PA (hence the name linear crosstalk). In Fig. 1., the linear crosstalk is associated with the scaling factors $\alpha_i$ and $\beta_i$.

b. Nonlinear crosstalk: This kind of crosstalk occurs before the nonlinear TX components (mainly the PA). Nonlinear crosstalk can occur due to leakage through the common local oscillator (LO) or radio frequency (RF) radiation from neighboring paths. The LO leakage would have equal magnitudes across all paths, whereas the radiation between the different paths decays the further it is moved away (i.e. the radiation coming to Path 1 from Path 3 in a three-MIMO TXs would be less than that due to Path 2) and is assumed to be symmetrical (i.e. $\alpha_{NL}$ and $\beta_{NL}$ in Fig. 1. are equal). Typical values of crosstalk are between-15 and -30 dB [18].

In this paper, both types of crosstalk are considered. As the extension of behavioral models describing systems with nonlinear crosstalk to the linear crosstalk case is straightforward (as has been shown in the literature [10]), the models are developed for the nonlinear crosstalk case in this paper, and results for both the linear and nonlinear crosstalk cases are presented.

B. MIMO Transmitter Models in the Literature

1) Cross-over Memory Polynomial Model (CO-MPM)

In this model, the output of each amplifier is approximated as the sum of two nonlinear functions. Starting with Fig. 1. and considering only the nonlinear crosstalk at the input of the PAs, the output of the first PA can be written as

\[
y^{(1)}(n) = f_{PA_1} (x_1(n) + \beta_{NL} x_2(n))
\]

\[
y^{(2)}(n) = f_{PA_2} (x_2(n) + \alpha_{NL} x_1(n))
\]

where $x_1(n)$ and $x_2(n)$ are the inputs, $y^{(1)}(n)$ and $y^{(2)}(n)$ are the outputs of each power amplifier, and $f_{PA_1}$ and $f_{PA_2}$ are the nonlinear functions representing each PA. Considering the crosstalk to be symmetrical as explained previously, the output of the two PAs using the cross-over model is

\[
y^{(1)}(n) = f_{11} (x_1(n)) + \beta_{NL} f_{12} (x_2(n))
\]

\[
y^{(2)}(n) = f_{22} (x_2(n)) + \alpha_{NL} f_{21} (x_1(n))
\]

where each of the functions $f_{11}, f_{12}, f_{21}$ and $f_{22}$ are built using the memory polynomial model. The expression for $y^{(1)}(n)$ now becomes [12]

\[
y^{(1)}_{CO-MPM} (n) = \sum_{m=0}^{M-1} \sum_{k=0}^{N} a_{m,k}^{(1)} (\alpha_{NL} x_1(n-m) + \beta_{NL} x_2(n-m))^{2k}
\]

where $M$ is the memory depth, $N$ is the nonlinearity order and $a_{m,k}^{(1)}, b_{m,k}^{(1)}$ are the coefficients of each branch of the model, noting that the crosstalk scaling factor $\beta_{NL}$ is embedded in the set of coefficients $b_{m,k}^{(1)}$ in [10][16]. As can be seen from (2) and (3), CO-MPM approximates the output of a two-input single-output nonlinear function as two single-input single-output nonlinear memory polynomial model (MPM) functions, neglecting the interactions of the two signals at the input. As a result, this model requires relatively few coefficients and has a reasonable implementation cost. However as the approximation used to define the model holds only for weak levels of crosstalk, it can be expected that the performance will degrade when the crosstalk at the input is stronger than about -20 dB, which is expected to occur for the high levels of integration foreseen in 5G systems and beyond [1].

Fig. 1. Block diagram of a 2xK MIMO transmitter with linear and nonlinear crosstalk.
2) 2x2 Parallel Hammerstein Model (2x2 PH)

In order to better model MIMO transmitters with wider range of crosstalk, [16] proposed an inclusive MIMO model using multi-input polynomial model instead of the single-input MPM used in the crossover model. Using the same notation, in the case of 2xK system the output of the first PA using this model is

\[ y^{(1)}(n) = f_{11}(x_1(n), x_2(n)) + \beta_{NL} f_{12}(x_1(n), x_3(n)) \]  

(4)

\[ y^{(1)}_{12-20}(n) = M \sum_{m=0}^{N-1} \sum_{k=0}^{K-1} a_{m,k}^{(1)} x_1(n-m) x_2(n-m) x_3(n-m) + \sum_{m=0}^{N-1} \sum_{k=0}^{K-1} b_{m,k}^{(1)} x_1(n-m) x_2(n-m) x_3(n-m) \]

where \( y^{(1)}_{12-20}(n) \) represents the estimate of \( y^{(1)}(n) \) using the 2x2 PH model. Examining (5), we can notice that this model requires a larger number of coefficients due to the use of a triple summation. An additional issue associated with this model is that it would be difficult to use it for larger MIMO systems. This issue of model complexity is discussed in further detail in Section III.C.

III. PROPOSED AUGMENTED CROSS-OVER MEMORY POLYNOMIAL MODEL

As can be inferred from the previous discussion, there is a need for behavioral models which can achieve a balance between the low complexity of CO-PM, and the superior performance of multiple-input structures as the 2x2 PH model, motivating the development of the model proposed in this paper. In this section, an augmented polynomial model which achieves similar accuracy as 2x2 PH while requiring the same number of coefficients as CO-PM is developed.

A. Model Derivation

Revisiting (1) and using an MPM function to represent \( f_{PA} \), the output of the first PA, \( y^{(1)}(n) \), is written as

\[ y^{(1)}(n) = \sum_{m=0}^{N-1} \sum_{k=0}^{K-1} a_{m,k}^{(1)} (x_1(n-m) + \beta_{NL} x_2(n-m)) \]

(6)

Setting \( j = n-m \), expanding and rearranging, we obtain

\[ y^{(1)}(n) = \sum_{m=0}^{N-1} \sum_{k=0}^{K-1} a_{m,k}^{(1)} (x_1(j) + \beta_{NL} x_2(j)) \]

(7)

which is the first step in deriving the CO-PM expression.

Continuing by expanding \( (x_1(j) + \beta_{NL} x_2(j))^2 \) using the multinomial expansion theorem and setting

\[ z(j) = (x_1(j) + \beta_{NL} x_2(j)) \]

where \( k \) is the index of the nonlinearity order as defined in (3) and (4), and the indices \( k_1, k_2, k_3 \) are interim summation indices. Considering even in the worst case the crosstalk is around -15 dB in a realistic MIMO system, terms corresponding to \( \beta_{NL} \) would translate to negligible crosstalk of -45 dB or below. Thus, we can neglect these terms and any others having higher powers. By expanding (8.b) above, neglecting terms corresponding to \( \beta_{NL} \) and higher powers, substituting in (7) and collecting the terms as detailed in Appendix A, we arrive at the expression for the model output

\[ y^{(1)}(n) = \sum_{m=0}^{N-1} \sum_{k=0}^{K-1} a_{m,k}^{(1)} (x_1(j) + \beta_{NL} x_2(j)) \]

(8.a)

\[ \times \left[ 1 + \phi(j) + \psi(j) \right] \]

(9)

substituting for simplicity

\[ \phi(j) = x_1^2(j)x_2(j) + x_2^2(j)x_1(j) \]

\[ \psi(j) = x_1^2(j)x_2(j) + x_2^2(n)x_1(j) + x_2(j)^2 \left[ 1 + x_1(j)^2 \right] \]

(10)

noting that the crosstalk factors are incorporated into the model coefficients. This model, referred to as the augmented crossover MPM (A-COMPM), improves upon CO-PM by incorporating nonlinear ‘cross’ terms which account for the interaction between the two signal paths, allowing for more accurate modeling of MIMO transmitters suffering from crosstalk effects, while requiring the same number of coefficients as CO-PM.

In contrast to 2x2 PH, the basis functions of this model do not follow a generalized two-input structure and consider the nature of the crosstalk in the formulation, and thus directly model the system using less coefficients. It is important to note that the crosstalk coefficients are incorporated into the model coefficients \( a_{m,k}^{(1)} \) similarly to CO-PM and 2x2 PH and thus do not need to be estimated independently.

The extension of models describing nonlinear crosstalk in MIMO to the case with crosstalk, which is simple and has been discussed previously in the literature [10]

B. Model Complexity

In this section, the models discussed are compared in terms of their relative complexity, which in this paper refers to the number of coefficients required for each model. With the push towards 5G systems utilizing wider signal bandwidths and...
massive MIMO, it is crucial to take the model complexity into account to ensure feasibility of implementation when the models (and DPDs based on them) are scaled up for higher-order MIMO scenarios. Examining the equations for the three models ((3), (5) and (9)), the number of coefficients needed by each model can be calculated as follows.

\[ C_{CO-MPM} = 2M(N+1) \]
\[ C_{A-COMPM} = 2M(N+1) \]
\[ C_{2x2-PH} = \frac{M(N+1)(N+2)}{2} \] (11)

From (11) above, we can see that the proposed A-COMPM requires the same number of coefficients as CO-MPM and significantly less than the 2x2 PH model (and, by extension, similar multiple-input model structures reported in [10]). Thus, the resources required to implement A-COMPM would be equal to CO-MPM and much lower than the 2x2 PH model.

To illustrate, the number of coefficients required by the three models for various values of \( M \) and \( N \) are given in Table I. From this table, we can see that the 2x2 PH model requires more than triple the number of coefficients as CO-MPM and A-COMPM for equal choices of \( M \) and \( N \). This also indicates that for highly nonlinear transmitters with strong memory effects, the 2x2 PH model would not be an efficient choice since such cases require high values of \( M \) and \( N \).

Furthermore, this issue of complexity gains additional importance from the fact that (as shown in [10]) the compensation of linear crosstalk doubles the number of coefficients. This motivates the need for models using a low number of coefficients even further, and supports the value of the proposed model.

Another important aspect to consider is the scalability of the models as the size of the MIMO systems grows. Examining equation (5) representing the 2x2 PH model, we can see that three inner summations are needed for the 2xK MIMO case. If we move further to 3xK MIMO and beyond, this means that additional inner summations will need to be added for each additional path, and the 3x3 PH model would thus require \( M(N)(N+1)(N+2) \) for each branch, which means that the number of coefficients required increases exponentially. Conversely, A-COMPM and CO-MPM scale linearly to the order of \( MN \). This indicates that for large-scale and Massive MIMO systems, which are expected to be used for 5G systems and beyond, efficient structures such as the proposed A-COMPM are necessary to ensure feasible implementation, and multiple-input structures would be less viable.

**C. Model Identification**

The general matrix form of a behavioral model is

\[ y_i = A_i w_i \] (12)

where \( y_i \) is the \( L \times 1 \) vector representing the samples of the output of the \( i \)-th PA, \( A_i \) is the \( L \times S \) matrix representing each of the models (where \( S \) is the total model size), and \( w_i \) is an \( S \times 1 \) vector containing the coefficients corresponding to each model. For simplicity, the \( i \) subscript is dropped in subsequent equations. The structures of the respective model matrices are given below

\[ A^{(1)}_{CO-MPM} = \begin{bmatrix} A^{(1)}_{CO-MPM} & A^{(2)}_{CO-MPM} \\ \end{bmatrix} \]
\[ A^{(1)}_{A-COMPM} = \begin{bmatrix} A^{(1)}_{CO-MPM} & A^{(2)}_{A-COMPM} \\ \end{bmatrix} \]
\[ A^{(1)}_{2x2-PH} = \begin{bmatrix} A^{(1)}_{2x2-PH} & A^{(2)}_{2x2-PH} \\ \end{bmatrix} \] (13)

where one row of each of the component matrices (corresponding to one time index \( j = n-m \) ) is given

\[ A^{(1)}_{CO-MPM} (j) = \begin{bmatrix} x_i(j) & \cdots & x_i(j)x_i(j)^2 & \cdots & x_i(j)x_i(j)^N \end{bmatrix} \]
\[ A^{(2)}_{CO-MPM} (j) = \begin{bmatrix} x_i(j) & \cdots & x_i(j)x_i(j)^2 & \cdots & x_i(j)x_i(j)^N \end{bmatrix} \]
\[ A^{(1)}_{A-COMPM} (j) = \begin{bmatrix} x_i(j) & \cdots & x_i(j)x_i(j)^2 & \cdots & x_i(j)x_i(j)^N \end{bmatrix} \theta(j) \]
\[ A^{(2)}_{A-COMPM} (j) = \begin{bmatrix} x_i(j) & \cdots & x_i(j)x_i(j)^2 & \cdots & x_i(j)x_i(j)^N \end{bmatrix} \theta(j) \]
\[ A^{(1)}_{2x2-PH} (j) = \begin{bmatrix} x_i(j) & \cdots & x_i(j)x_i(j)^2 & \cdots & x_i(j)x_i(j)^N \end{bmatrix} \theta(j) \]
\[ A^{(2)}_{2x2-PH} (j) = \begin{bmatrix} x_i(j) & \cdots & x_i(j)x_i(j)^2 & \cdots & x_i(j)x_i(j)^N \end{bmatrix} \theta(j) \] (14)

where \( \theta(j) \) and \( \theta(j) \) are

\[ \theta(j) = 1 + \beta_{NL}(\phi(j)) + \beta_{2NL}(\psi(j)) \]
\[ \theta(j) = \beta_{NL} + \beta_{2NL}(\phi(j)) \] (15)

After constructing the model matrices as outlined above, the coefficients are typically extracted using the well-known method of least squares (LS) [19] as follows

\[ \hat{w}_i = (A_i^\top A_i)^{-1} A_i^\top y_i \] (16)

The LS method has been extensively used to extract the parameters of behavioral models and DPDs. However, it is known to suffer from numerical stability issues due to the matrix inversion step when large and/or ill-conditioned model matrices are involved. This issue is discussed next.
D. Model Condition Number and Numerical Instability Issues

For a given behavioral model, the condition number is defined as:

\[
\text{Condition Number}_{\text{dB}} = 10 \log_{10} \left( \left\| A \right\| \left\| A^{-1} \right\| \right) \tag{17}
\]

A high condition number for a model indicates that it model can suffer from numerical instability issues in the extraction process, and that the model would need a large number of bits (e.g., 32 bits in some cases as reported in [21]), which would increase the implementation cost. This issue was investigated in depth for MIMO systems in [14]. In Fig. 2., the condition number of the three models for a fixed memory depth \( M = 2 \) and a nonlinearity order between 5 and 10. From this figure, we can see that the proposed A-COMPM has a substantially lower condition number than the 2x2 PH model (less by 15 dB), and maintains a close condition number to CO-MPM. This suggests that the proposed model is more numerically stable and that it can be implemented reliably on a fixed-point processor. In [20] an approach based on signal processing was proposed for reducing the condition number of model matrices and improving the numerical stability of the extraction, which was then extended to the MIMO case in [21]. In [17], orthogonal basis functions were used for the same purpose.

Fig. 2. Condition number of the three models as a function of the nonlinearity order \( N (M=2) \).

IV. EXPERIMENTAL VALIDATION

A. Experimental Setup

In this experiment, two identical ZHL-42 amplifiers were driven by two single-carrier 20 MHz LTE signals using the setup depicted in Fig. 3. The signals were sampled at 92.16 MHz, and then sent at a carrier frequency of 2.425 GHz using two time- and phase-aligned Agilent ESG4438C signal generators connected to a computer. The two generators were then connected with couplers which introduce varying levels of crosstalk from −15 dB to −30 dB on the RF signals before being sent to the PAs. Subsequently, the output of the two PAs was connected through couplers, and the output of each coupler was captured and time-aligned with the input signal, in preparation for model extraction using the MATLAB 2014a™ software. The DPD is constructed using the well-known indirect learning architecture (ILA) through the same methodology in [12][14][16].

B. Performance Metrics Used

1) Normalized Mean Square Error (NMSE)

The NMSE is a time-domain metric which is commonly used in the literature to quantify the accuracy of behavioral models [22]. NMSE is defined as

\[
\text{NMSE}_{\text{dB}} = 10 \log_{10} \frac{\sum_{n=1}^{L} |y(n) - \hat{y}(n)|^2}{\sum_{n=1}^{L} |y(n)|^2} \tag{18}
\]

where \( y(n) \) is the measured output, and \( \hat{y}(n) \) is the estimated output obtained using the models. Typically, values of NMSE below −40 dB are desirable [22].

2) Adjacent Channel Power Ratio (ACPR)

To study the linearization performance of a DPD, the ACPR metric is commonly used in the literature [22].

\[
\text{ACPR}_{\text{dB}} = 10 \log_{10} \left[ \frac{\int_{\text{adj channel}} |Y(f)|^2 \, df}{\int_{\text{main channel}} |Y(f)|^2 \, df} \right] \tag{19}
\]

The ACPR can be evaluated for the adjacent channels above and below the main carrier (known as the upper and lower ACPR), in units of dBC (dB below the carrier). The long-term evolution (LTE) standard requires an ACPR < −45 dBC.

C. Modeling Results

1) Modeling performance in the presence of crosstalk

To compare the three models, the LTE signals were sent through the PAs using different levels of crosstalk ranging from −15 dB to −30 dB. In order to represent a realistic scenario, crosstalk weaker than −30 dB was not considered in this paper. Subsequently, the models were then used to fit the input and output data (i.e., forward modeling). In this experiment, the M and N were chosen as 8 and 8 respectively, to ensure that each model achieves its best possible performance. The results of this experiment are given in Fig. 4. The immediate observation to be made is that for the case of the strongest crosstalk (−15 dB), A-COMPM outperforms CO-MPM by around 5 dB in terms of modeling accuracy, which represents a substantial improvement in performance. In addition, we can see that the performance of CO-MPM degrades as the crosstalk grows stronger, whereas the
proposed A-COMPM and 2x2 PH models maintain their accuracy. This is to be expected due to the approximation used in deriving CO-MPM as discussed in Section II.B. Furthermore, we can observe that even for the weakest crosstalk used in this study (−30 dB), A-COMPM still outperforms CO-MPM by around 1 dB.

**Fig. 4.** Impact of increasing the nonlinear crosstalk on the modeling accuracy of the three models

2) **Model complexity**

To compare the various models in terms of complexity, the memory depth and nonlinearity order parameters, \( M \) and \( N \), were swept from 1 to 8, and the best NMSE for a given number of coefficients was recorded. The results of this experiment for −15 dB of crosstalk are given in Fig. 5, which shows the NMSE for each model as a function of the number of coefficients required. Observing this figure, we can see that overall, the proposed A-COMPM achieves consistently better performance than CO-MPM. Compared to the 2x2 PH model, A-COMPM achieves better (or similar in the worst case) performance for a lower number of coefficients; with a reduction of around 30% in some cases being achieved (such as in the −15 dB case).

Observing these results, it is evident that ACO-MPM outperforms both models while using a low number of coefficients; meaning that it combines the advantages of both models and presents a viable and attractive alternative for modeling MIMO transmitters with crosstalk.

**Fig. 5.** NMSE performance as a function of the number of coefficients for the various models in the presence of -15 dB nonlinear crosstalk.

**D. Linearization Results**

After testing the performance of the models in the forward direction, the DPDs based on them were then built and used to linearize the two MIMO transmitters described in the beginning of this section. In this experiment, the nonlinear crosstalk was set as −15 dB, and the linear crosstalk was −20 dB and the linearization experiment was performed three times, covering three scenarios:

- **Scenario A:** Both linear and nonlinear crosstalk are present.
- **Scenario B:** Only nonlinear crosstalk is present.
- **Scenario C:** Only linear crosstalk is present.

The size of each of the models was set to 80 coefficients to compare how they perform for an equal number of basis functions. For the 2x2 PH DPD, an extra set of measurements was performed in order to study the performance of the model at a size of 252 coefficients, to enable it to achieve better performance. The results of this linearization experiment are

**Fig. 6.** Linearization performance of the various predistorters for different scenarios: (a) -15 dB nonlinear crosstalk and -20 dB linear crosstalk. (b) -15 dB nonlinear crosstalk. (c) -20 dB linear crosstalk.
TABLE II
LINEARIZATION RESULTS FOR THE VARIOUS DPDs

<table>
<thead>
<tr>
<th>Model</th>
<th>M</th>
<th>N</th>
<th>No. of Coefficients</th>
<th>ACPR (dBc)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Scenario (A)</td>
</tr>
<tr>
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<td>Lower</td>
</tr>
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<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>-35.03</td>
</tr>
<tr>
<td>CO-MPM</td>
<td>5</td>
<td>8</td>
<td>80</td>
<td>-41.58</td>
</tr>
<tr>
<td>A-COMPM</td>
<td>5</td>
<td>5</td>
<td>80</td>
<td>-47.24</td>
</tr>
<tr>
<td>2x2 PH</td>
<td>4</td>
<td>4</td>
<td>80</td>
<td>-41.50</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>6</td>
<td>252</td>
<td>-47.24</td>
</tr>
</tbody>
</table>

given in Fig. 6 and Table II, which show the spectra of the linearized signals and numerical values of the ACPR achieved by the three predistorters.

From these results across the three scenarios, we can see that the A-COMPM DPD significantly outperforms CO-MPM by a margin of around 6 dB in terms of linearization performance. Compared to 2x2 PH, the proposed model outperforms it by the same margin as CO-MPM when 2x2 PH is limited to a size 80 coefficients. From the results, we can see that 2x2 PH needs about three times as many coefficients as the proposed model to achieve comparable performance. This suggests that the A-COMPM DPD achieves convergence and performs better while needing a lower number of coefficients. As a result of this enhanced performance, the A-COMPM DPD succeeds in meeting the spectral emission requirement of the LTE standard (i.e. an ACPR < -45 dBc), whereas CO-MPM and the 2x2 PH model fail to do so for the same number of coefficients, which impacts their viability for being used in practical communication systems.

V. SUMMARY AND CONCLUSIONS

In this paper, we have developed a new behavioral model for nonlinear MIMO transmitters with crosstalk, known as A-COMPM. This model uses novel basis functions to better incorporate the effect of nonlinear crosstalk into CO-MPM. We have shown that the proposed model significantly outperforms CO-MPM in the presence of strong nonlinear crosstalk in terms of modeling accuracy, and achieves comparable performance to the 2x2 PH model while requiring a lower number of coefficients. From the results presented, the significance of the proposed augmented CO-MPM DPD as an efficient yet powerful choice for linearizing MIMO transmitters becomes evident. Building on this model, future avenues for research include extending the model for higher-order MIMO cases.

APPENDIX A

DERIVATION OF THE A-COMPM EXPRESSION

In this appendix, the details of the derivation of A-COMPM are provided. Starting with (8.a) and setting \( j = n - m \):

\[
|z(j)|^2 = |z(j)^\ast(j)| = (x_1(j) + \beta_{NL} x_2(j)) (x_1^\ast(j) + \beta_{NL} x_2^\ast(j))
\]

\[
= \left| x_1(j)^2 \right| + \beta_{NL}^2 x_2(j) x_1^\ast(j) + \beta_{NL} x_1(j) x_2^\ast(j) x_1^\ast(j) + \beta_{NL} x_2(j) x_1^\ast(j) x_2^\ast(j) x_1^\ast(j)
\] (20)

\[
|z(j)|^2 = \sum_{k=0}^{\infty} \sum_{k_1=0}^{\infty} \sum_{k_2=0}^{\infty} \sum_{k_3=0}^{\infty} \sum_{k_4=0}^{\infty} \left( \beta_{NL} \right)^2 |x_1(j)|^2 h^k \left( x_2(j) x_1^\ast(j) x_2^\ast(j) x_1^\ast(j) \right)^k
\]

(21.a)

Rearranging

\[
|z(j)|^2 = \sum_{k=0}^{\infty} \sum_{k_1=0}^{\infty} \sum_{k_2=0}^{\infty} \sum_{k_3=0}^{\infty} \sum_{k_4=0}^{\infty} \left( \beta_{NL} \right)^2 |x_1(j)|^2 h^k \left( x_2(j) x_1^\ast(j) x_2^\ast(j) x_1^\ast(j) \right)^k
\]

(21.b)

As mentioned in Section II.B., we are only considering terms up to \( \beta_{NL} \), which leads to the condition \( 2k_2 + k_3 + k_4 \leq 2 \).

According to this condition, we can have the following values for \( k_2, k_3, k_4 \): \( (0,0,0), (0,1,0), (0,0,1), (1,0,0), (0,1,1), (2,0,0), \) and \( (0,0,2) \). Using these values, we obtain the following terms

\[
|z(j)|^2 = \sum_{k=0}^{\infty} |x_1(j)|^2 \left[ 1 + \beta_{NL} x_1^\ast(j) x_2(j) + \beta_{NL} x_2^\ast(j) x_1(j) + \beta_{NL} x_1^\ast(j) x_2^\ast(j) x_1^\ast(j) + \beta_{NL} x_2(j) x_1^\ast(j) x_2^\ast(j) x_1^\ast(j) \right]
\]

(22.a)

Rearranging the terms

\[
|z(j)|^2 = \sum_{k=0}^{\infty} |x_1(j)|^2 \left[ 1 + \beta_{NL} \left( x_1^\ast(j) x_2(j) + x_2^\ast(j) x_1(j) \right) + \beta_{NL} \left( x_1^\ast(j) x_2(j) x_1^\ast(j) \right)^2 \right]
\]

(22.b)

For simplicity and convenience, we rewrite the above equation as

\[
|z(j)|^2 = \sum_{k=0}^{\infty} |x_1(j)|^2 \left[ 1 + \beta_{NL} \left( \phi(j) \right) + \beta_{NL}^2 \left( \psi(j) \right) \right]
\]

(22.c)

Now, we substitute in (7)
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REFERENCES


