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PERFORMANCE-DRIVEN DIMENSION ESTIMATION OF MEMORY POLYNOMIAL BEHAVIORAL MODELS FOR WIRELESS TRANSMITTERS AND POWER AMPLIFIERS

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Abstract—A novel approach is proposed for automated dimension estimation in memory polynomial based power amplifiers/transmitters behavioral models. This method consists of successively identifying the static nonlinearity order and memory depth of the model in accordance with a predefined performance criterion. The proposed method is validated using a 3G Doherty power amplifier driven by various WCDMA signals. Experimental results demonstrate the robustness of the proposed successive sweep approach compared to the conventional blind simultaneous sweep approach. The proposed dimension estimation method is an enabling tool for efficient design optimization of power amplifiers circuits to enhance their linearizability.

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1. INTRODUCTION

Power amplifiers (PAs) are one of the major sources of nonlinearity in communication systems, and their nonlinearity can significantly affect system performance. Since the linearity of a transmitter has to meet stringent spectrum emission requirements, it is essential to accurately predict and compensate for the nonlinearities of the amplification circuit. The compensation for PA nonlinearities is performed using a linearization technique [1–3]. Among the various techniques reported in the literature, digital predistortion is the one that currently achieves the best trade-off, in terms of performance, complexity and cost-effectiveness [4–11]. This technique consists of using a complementary nonlinearity upstream of the nonlinear device under test (DUT), so that the cascade of the predistorter and DUT behaves as a linear system. Several model structures have been widely used for both power amplifiers modeling and digital predistorters implementation. These models include look-up tables (LUT), memoryless polynomial, memory polynomials, etc. [4–14]. This work primarily focuses on the behavioral modeling of nonlinear PAs/transmitters. However, all the results derived can be transposed to digital predistortion applications.

Due to the wide bandwidths of the signals that are being used for wireless communication infrastructure applications, the PA/transmitter exhibits, in addition to conventional static nonlinear distortions, dynamic nonlinearities commonly referred to as memory effects. A key step in the behavioral modeling of wireless communication transmitters is the selection of an appropriate model that best describes and accurately simulates PA performance. This selection includes the choice of model architecture and dimensions. Numerous behavioral models have been proposed in the literature, including the Volterra model, the memory polynomial model, the orthogonal memory polynomial model, the Wiener model, the Hammerstein model and the augmented Hammerstein model [4–14]. Wiener and Hammerstein models assume that the behavior of the DUT can be described as the cascade of a static nonlinear function and a linear filter. This assumption on the nature of the DUT behavior limits the applicability of these two-box models and contrasts with the single box approach of memory polynomials and Volterra based models for which there is no such assumption.

The Volterra model is a general and comprehensive model for dynamic nonlinear systems that often leads to significant complexity, especially for high-order nonlinearities. Accordingly, in practice, Volterra series are only used for modeling weakly nonlinear systems. Conversely, memory polynomials, which result from considering only the diagonal terms of the Volterra model, lead to a significant reduction in the model complexity while keeping reasonable modeling accuracy and performance. For these reasons, memory polynomial models are among the most widely used structures for PA modeling and digital predistortion.

For all behavioral models in general and memory polynomial based models in particular, it is essential to accurately determine the optimal model dimensions. In the case of memory polynomial models, the model dimensions are defined by the nonlinearity order and memory depth. These depend not only on the DUT, but also on the operating conditions.

In this paper, a highly nonlinear Doherty PA is characterized using several Wideband Code Division Multiple Access (WCDMA) signals with different carrier configurations and bandwidths spanning from 5 to 20 MHz. A novel approach is proposed for the accurate estimation of the model dimensions. To the best of the authors' knowledge, this is the first systematic approach for dimension estimation of memory polynomial models. The proposed method successively estimates the nonlinearity order and then the memory depth of the DUT's memory polynomial model. It is demonstrated that this approach leads to accurate dimension estimation that maximizes a predefined performance metric (in this case, minimizes the normalized mean squared error (NMSE) between the measured and estimated output waveforms). The model dimension estimation method is validated for each of the considered WCDMA signals. The results illustrate the anticipated dependency between the memory depth of the DUT and the driving signals' bandwidths. The proposed approach for model dimension estimation can efficiently provide the analog RF circuit designer with important information about the nonlinear behavior of the system and especially the complexity of the required linearization circuit. This information can be used to guide the amplification circuit tuning in order to improve its linearizability without affecting its performances in terms of power efficiency.

In Section 2, the experimental setup and test conditions are presented. The proposed model dimension estimation is introduced in Section 3. In Section 4, the proposed algorithm is applied to model the DUT when driven by various test signals. The conclusions are reported in Section 4.

2. MEASUREMENT SETUP AND TEST CONDITIONS

Several WCDMA waveforms were used to characterize the DUT and identify its behavioral models. These signals had different carrier configurations with bandwidths varying from 5 MHz, in the case of the single-carrier signal, to 20 MHz for the four-carrier signal. The carrier configurations of these signals, their respective bandwidths and peak-to-average power ratios (PAPR) are reported in Table 1. For the description of the carrier configurations, "1" refers to an ON carrier and "0" to an OFF carrier. For each signal, a three-slot waveform, which is 2 ms long, was used. All signals were sampled at 92.16 MHz, and only 10,000 samples out of the 184,320 samples of the input and output baseband waveforms were used for the model identification.

During the model validation step, the entire waveform was used to assess the robustness of the model. For each drive signal, the DUT was characterized using the standard instantaneous input and output baseband complex waveforms technique.

Table 1. Carrier configuration and PAPR of the WCDMA test signals.

Signal ⇓	Carrier Configuration	Bandwidth	PAPR
1-Carrier	010	5 MHz	10.4 dB
2-Carrier	11	10 MHz	10.4 dB
3-Carrier	111	15 MHz	10.6 dB
3-Carrier	101	15 MHz	10.5 dB
4-Carrier	1111	20 MHz	11.2 dB
4-Carrier	1001	20 MHz	10.8 dB

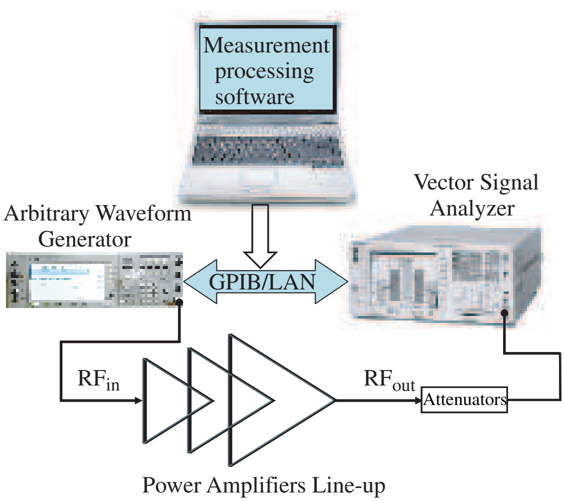


Figure 1. Experimental setup for DUT characterization.

The experimental setup used in this work is shown in Fig. 1. The baseband input waveform is downloaded into the arbitrary waveform generator that feeds the device under test with the modulated RF signal. The DUT's output signal is processed within a vector signal analyzer where the signal down-conversion, digitization and demodulation are performed. The resulting baseband waveform is then processed by dedicated software to extract the behavioral models of the DUT.

Figure 2 presents the complementary cumulative distribution function (CCDF) of the considered test signals. Accordingly, it appears that the statistics of the signals are close enough to avoid any changes in the observed PA behavior that can be attributed to the variation of the test signals' statistics. Indeed, the behavior of the PA is insensitive to such variations in the signal's CCDF [15]. Moreover, all measurements were performed at a constant average power around the same carrier frequency. This ensures that any changes observed in the PA behavior are solely due to the signal bandwidths.

Two measured AM/AM characteristics of the DUT are presented in Fig. 3. These correspond to the raw data (after accurate time delay alignment) measured with 1-carrier and 4-carrier (1001) drive signals. As demonstrated by the dispersion observed in these figures, the DUT presents mild memory effects when driven by the 1-carrier signal and strong memory effects when driven by the 4-carrier signal.

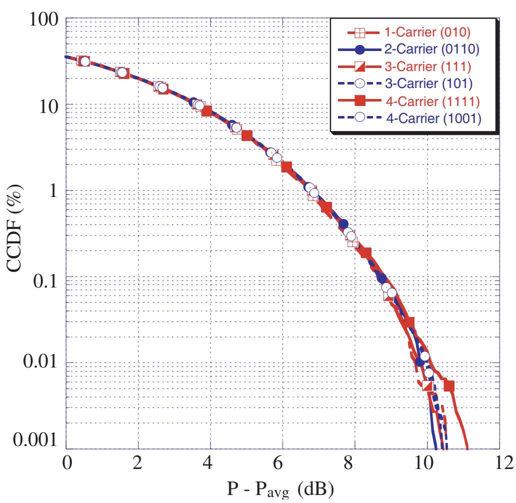
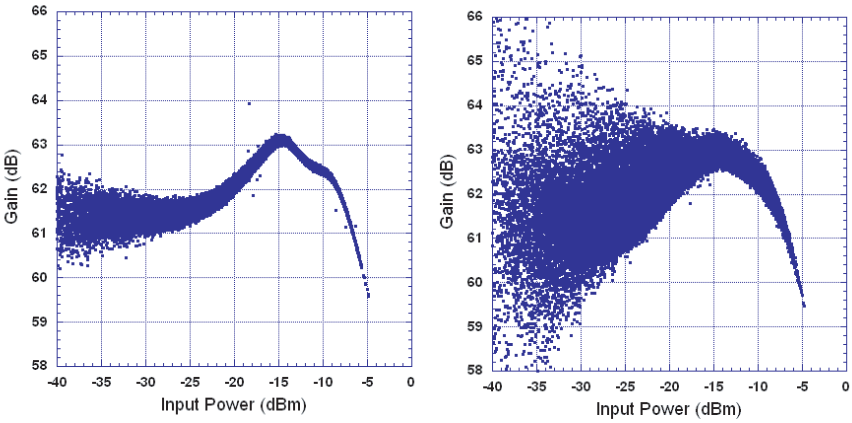


Figure 2. CCDF of the WCDMA test signals.



(a) (b)

Figure 3. Measured AM/AM characteristics of the DUT. (a) under WCDMA 1-Carrier drive. (b) under WCDMA 4-Carrier (1001) drive.

3. ALGORITHM FOR MEMORY POLYNOMIAL MODEL DIMENSION ESTIMATION

Memory polynomial models are defined with two dimensions: the nonlinearity order (N) and the memory depth (M). It is essential to accurately identify the model dimensions in order to avoid over- or under-modeling of the system. In this work, a novel approach for model dimension estimation is proposed. It is based on successively estimating the nonlinearity order (N_{opt}) and the memory depth (M_{opt}) of the memory polynomial model. The output waveform $\left[y_{est,N_{opt},M_{opt}}(n)\right]$ of the memory polynomial model is expressed in terms of the input signal $[x(n)]$ and the model coefficients (a_{ji}) according to:

$$y_{est,N_{opt},M_{opt}}(n) = \sum_{j=0}^{M_{opt}} \sum_{i=1}^{N_{opt}} a_{ji} \cdot x(n-j) \cdot |x(n-j)|^{i-1} \tag{1}$$

The flow chart of the proposed model dimension estimation algorithm is presented in Fig. 4. First, the DUT is characterized in order to estimate its nonlinearity order. For this, two approaches can be considered. The first, and most common, consists of using the actual test signal for which the PA's behavioral model is being derived. The second approach consists in using the corresponding signal that emulates a memory effects free behavior in order to excite its "true"

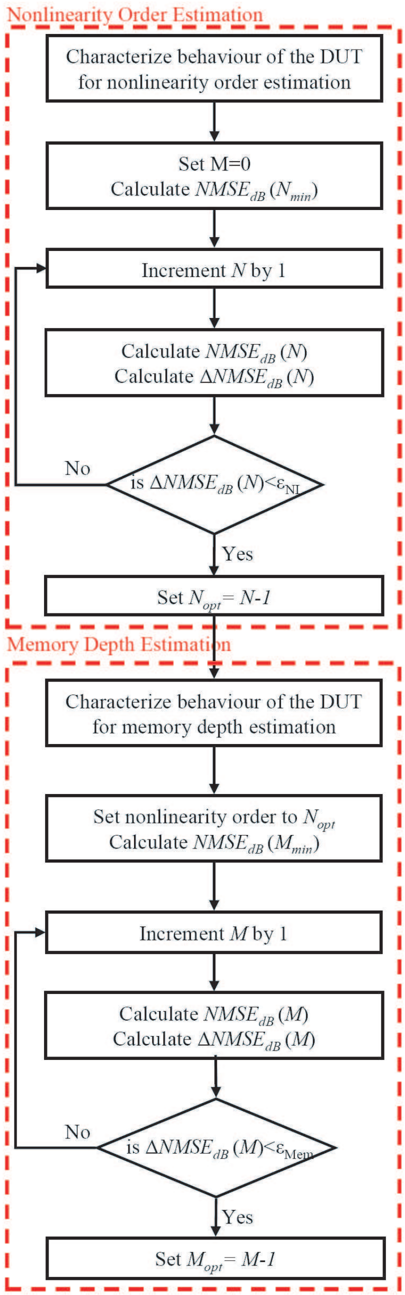


Figure 4. Flow chart of the proposed model parameters estimation algorithm.

static behavior. The emulation of the memory effects free behavior can be achieved by re-sampling the original waveform so that only its bandwidth is changed but not its statistics (CCDF) nor its average power [16, 17]. The bandwidth of the re-sampled signal is set to a value where the DUT does not exhibit neither electrical nor thermal memory effects. This bandwidth is typically around 1 MHz. In fact, below this value, thermal memory effects will appear. Conversely, for wider bandwidths electrical memory effects are typically observed. The validation of the memory effects free behavior of the DUT is achieved through memoryless digital predistortion [16]. It can be established that the DUT has a memory effects free behavior when no residual distortions are observed following memoryless digital predistortion.

Since the nonlinearity of power amplifiers is correlated with the memory effects, the use of the actual test signal for the nonlinearity order estimation will lead to a result that is biased by the observed memory effects. Conversely, the estimation of the nonlinearity order using the signal emulating a memory effects free behavior will correspond to an estimation of the effective nonlinearity order of the device under test that is not biased by the memory effects caused by the use of the actual test signal. Practically, both test signals were found to lead to similar results. Yet, the use of the signal emulating a memory effects free behavior is conceptually more correct.

The results of these measurements are then processed to extract the nonlinearity order of the memory polynomial based model. Later, in the next step where the memory depth is estimated, all the model coefficients including those of the first branch are identified for the new model dimension. The nonlinearity order is obtained by sweeping the nonlinearity order of a memoryless polynomial model. Each iteration consists of increasing the nonlinearity order (N) by 1 and estimating the corresponding NMSE [$\mathrm{NMSE_{dB}}(N)$], as well as the NMSE improvement [$\Delta\mathrm{NMSE}(N)$]. The $\mathrm{NMSE_{dB}}(N)$ and $\Delta\mathrm{NMSE}(N)$ are respectively given by:

$$\mathrm{NMSE_{dB}}(N) = 10\log_{10}\left(\frac{\sum_{i=1}^{K}\left|y_{meas}(i) - y_{est,N,0}(i)\right|^2}{\sum_{i=1}^{K}\left|y_{meas}(i)\right|^2}\right) \quad (2)$$

$$\Delta\mathrm{NMSE}(N) = \mathrm{NMSE_{dB}}(N-1) - \mathrm{NMSE_{dB}}(N) \quad (3)$$

where N and $y_{est,N,0}$ are the nonlinearity order and the estimated output waveform at the present iteration, respectively. y_{meas} is the measured output waveform, and K is the number of samples of the output waveforms.

The nonlinearity order (N) is swept until the performance metric improvement between two successive iterations satisfies a predefined selection criterion. In this case, the selection criterion is given by:

$$\Delta\text{NMSE}(N) < \varepsilon_{NL} \tag{4}$$

where ε_{NL} is a constant that corresponds to the minimum NMSE improvement between two consecutive steps. This parameter is used as a convergence criterion for the nonlinearity order estimation in the automated algorithm proposed for model dimension estimation. However, any other criterion or combination of criteria, either in time and/or frequency domains, can be implemented in this dimension estimation algorithm and used depending on the application requirements.

Once the nonlinearity order of the DUT is determined, the actual test signal is used to characterize the DUT. The nonlinearity order of the memory polynomial based model of the DUT is set to the value estimated in the previous step (N_{opt}). The memory depth is then determined iteratively in a manner similar to that used for determining the nonlinearity order. Each iteration consists of increasing the memory depth (M) by 1, estimating all the coefficients of the model, and calculating the corresponding NMSE $[\text{NMSE}_{\text{dB}}(M)]$, as well as the NMSE improvement $[\Delta\text{NMSE}(M)]$. The $\text{NMSE}_{\text{dB}}(M)$ and $\Delta\text{NMSE}(M)$ are defined as:

$$\text{NMSE}_{\text{dB}}(M) = 10\log_{10}\left(\frac{\sum\limits_{i=1}^{K}\left|y_{meas}(i) - y_{est,N_{opt},M}(i)\right|^2}{\sum\limits_{i=1}^{K}\left|y_{meas}(i)\right|^2}\right) \tag{5}$$

$$\Delta\text{NMSE}(M) = \text{NMSE}_{\text{dB}}(M-1) - \text{NMSE}_{\text{dB}}(M) \tag{6}$$

where M and $y_{est,N_{opt},M}$ are the memory depth and the estimated output waveform at the present iteration, respectively. y_{meas} is the measured output waveform, and K is the number of samples of the output waveforms.

The memory depth (M) is swept until the NMSE improvement satisfies a predefined selection criterion. In this case, the selection criterion is given by:

$$\Delta\text{NMSE}(M) < \varepsilon_{Mem} \tag{7}$$

where ε_{Mem} is a constant that corresponds to the minimum NMSE improvement between two consecutive steps. This parameter is used as a convergence criterion for the memory depth estimation in the automated algorithm proposed for model dimension estimation.

4. ALGORITHM FOR MEMORY POLYNOMIAL MODEL DIMENSION ESTIMATION

The proposed algorithm for model dimension estimation was applied to the DUT when driven by various WCDMA signals.

First, a narrowband signal was applied to the Doherty PA to emulate memory effects free behavior, as described in [17]. The nonlinearity order of the DUT was then derived according to the proposed algorithm.

For the considered tests, the convergence criteria were set to:

$$\begin{cases} \varepsilon_{NL} = 0.20 \\ \varepsilon_{Mem} = 0.05 \end{cases} \tag{8}$$

ε_{Mem} was set to value that is smaller than ε_{NL} for a better accuracy in the memory depth estimation. Indeed, the contribution of the static nonlinearity to the DUT behavior is significantly stronger than that of the memory effects.

The NMSE [$\text{NMSE}_{\text{dB}}(N)$], as well as the NMSE improvement [$\Delta\text{NMSE}(N)$], results are reported in Fig. 5. According to these results, the nonlinearity order of the DUT was found to be $N_{opt} = 9$.

The nonlinearity order was also evaluated using the same metrics (NMSE, ΔNMSE and ε_{NL}) when the DUT is driven by the various WCDMA signals. The NMSE and NMSE improvement results are reported in Figs. 6(a) and 6(b), respectively. For all WCDMA test signals except for the 4-carrier signal having the 1001 carrier configuration, it was observed that the use of the actual test signal

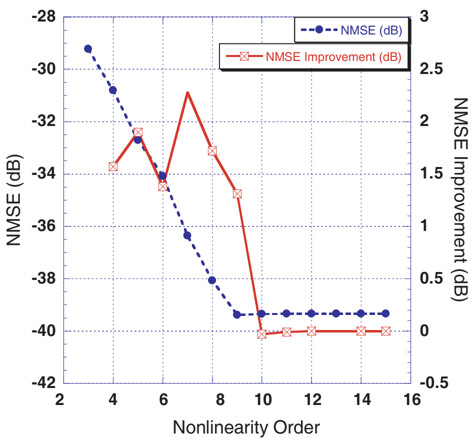
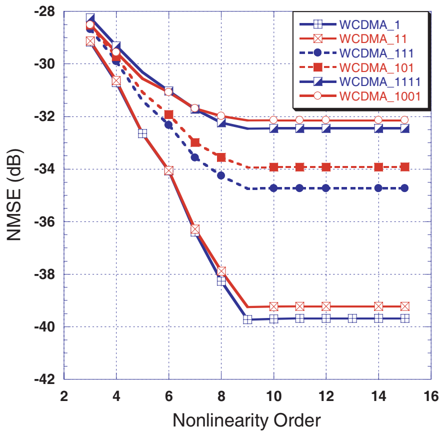
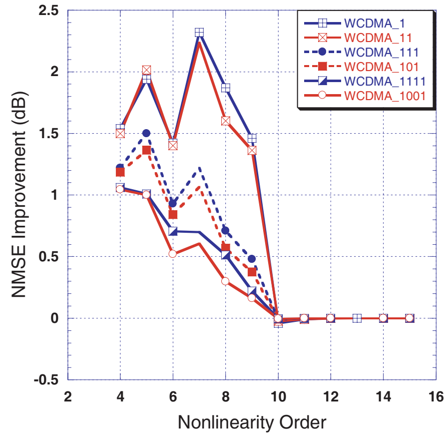


Figure 5. Calculated NMSE and NMSE improvement as a function of the model's nonlinearity order under memory effects free behavior.



(a)



(b)

Figure 6. Calculated performance of the models versus the nonlinearity order under the actual drive signal. (a) NMSE. (b) NMSE improvement.

for the nonlinearity order estimation led to the same results as the case where the DUT was driven by the narrow band signal. In fact, for the 4-carrier signal (WCDMA_1001) the optimal nonlinearity order was found to be 8 rather than 9. For this signal, which emulates the strongest memory effects intensity, the mismatch between the nonlinearity order estimated using the two approaches is mainly due to the considerable dispersion in the AM/AM characteristic as previously illustrated in Fig. 3(b). These results show that either the narrow band signal that emulates a memory effects free behavior of the DUT or the actual test signal can be used to estimate the nonlinearity order.

The memory effects intensity observed at the output of the DUT varied with the bandwidth and the carrier configuration of the drive signal. Thus, to validate the accurate estimation of the memory depth with the proposed algorithm, the six WCDMA drive signals presented in Section 2 were successively applied to the DUT. For each of these signals, the memory depth was determined using the proposed algorithm. In all these tests, the nonlinearity order of the DUT was set to $N_{opt} = 9$.

The NMSE $[\mathrm{NMSE}_{\mathrm{dB}}(M)]$ and NMSE improvement ($[\Delta\mathrm{NMSE}(M)]$) results are presented in Figs. 7(a) and 7(b), respectively. The model dimensions calculated, using the proposed algorithm and the convergence criteria defined in (8), for each of the considered test signals are summarized in Table 2. These results clearly illustrate the anticipated increase in the memory depth of the system as the bandwidth of the drive signal increases. More importantly, these results bring to light the effects of the power distribution within the modulation bandwidth on the memory depth exhibited by the DUT. Indeed, when OFF carriers are present in multi-carrier waveforms, the memory depth of the system is higher than that observed under a test signal with the same modulation bandwidth but with only ON carriers. This corroborates the results of the memory effects intensity (MEI) initially presented in [17]. Indeed, it was shown that, for a constant modulation bandwidth, the MEI increases when OFF carriers are present.

To further validate the proposed algorithm, a second approach was considered to determine the optimal model dimensions under the same WCDMA drive signals. This method consisted in simultaneously

Table 2. Model dimension versus drive signal.

Signal ⇓	Carrier Configuration	Model Dimension (M, N)
1-Carrier	010	(2, 9)
2-Carrier	11	(3, 9)
3-Carrier	111	(3, 9)
3-Carrier	101	(3, 9)
4-Carrier	1111	(3, 9)
4-Carrier	1001	(5, 9)

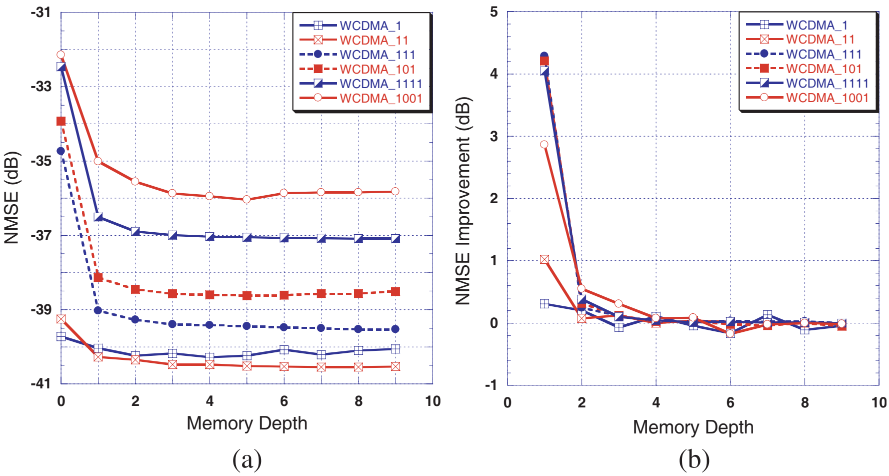


Figure 7. Calculated performance of the models versus the memory depth. (a) NMSE. (b) NMSE improvement.

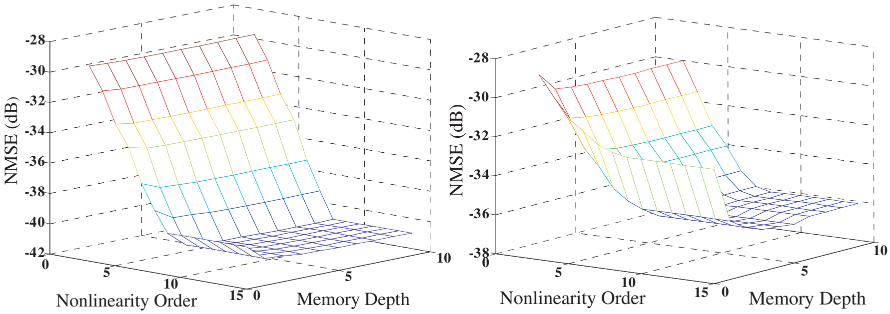


Figure 8. Calculated NMSE for the DUT model versus the nonlinearity order and the memory depth. (a) WCDMA11 signal. (b) WCDMA 1001 signal.

sweeping both the nonlinearity order and the memory depth over a wide range. This technique will herein be designated as the simultaneous sweep approach. In contrast, the proposed algorithm is designated as a successive sweep technique, since the nonlinearity order and the memory depth are determined successively. For the simultaneous sweep approach, the nonlinearity order of the DUT was swept from $N_{\min} = 3$ to $N_{\max} = 15$, and the memory depth was varied from $M_{\min} = 0$ to $M_{\max} = 9$.

For each test signal and (M, N) pair, a behavior model was extracted, and the NMSE between the measured and estimated output signals was calculated. This led to the identification of seven hundred and eighty (780) behavior models for the considered test signals. Fig. 8 presents the NMSE calculated for each combination of the nonlinearity order and the memory depth for the WCDMA 11 and WCDMA 1001 signals. As shown in this figure, the NMSE plots present a flat region in which the increase of either the nonlinearity order or the memory depth will not lead to any significant improvement in the NMSE performance. Similar plots were derived for all other test signals. These are not reported in this paper for conciseness.

Table 3 presents the results of the NMSE obtained with the proposed successive sweep approach and those obtained using the simultaneous sweep approach. In the latter case, the reported NMSE corresponds to its lowest value. The results presented in Table 3 show that the proposed successive sweep algorithm leads to quasi-optimal results, in terms of NMSE. Indeed, the NMSE difference between the two approaches is less than 0.2 dB.

Figure 9 shows the spectrum domain data for the WCDMA 11 and WCDMA 1001 test signals. In each plot, the spectra estimated using both models, derived using the successive and simultaneous sweep

Table 3. NMSE performance of the successive and simultaneous sweep techniques.

Carrier Configuration ⇓	Successive Sweep		Simultaneous Sweep	
	(M, N)	NMSE (dB)	(M, N)	NMSE (dB)
010	(2, 9)	−40.24	(3, 10)	−40.29
11	(3, 9)	−40.47	(8, 9)	−40.55
111	(3, 9)	−39.39	(8, 9)	−38.53
101	(3, 9)	−38.58	(5, 9)	−38.63
1111	(3, 9)	−36.99	(8, 9)	−37.09
1001	(5, 9)	−36.04	(5, 9)	−36.04

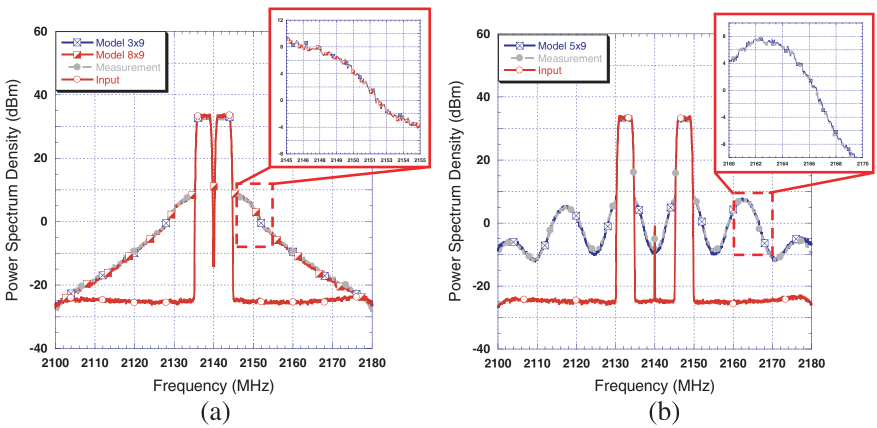


Figure 9. Model's performance assessment in frequency domain (a) WCDMA 11 signal using model parameters 3×9 (successive sweep), 8×9 (simultaneous sweep) along with the measured spectrum. (b) WCDMA 1001 signal using model parameters 5×9 (simultaneous and successive sweeps) along with the measured spectrum.

approaches, as well as the measured spectrum at the output of the DUT, are presented. According to this figure, the models derived using the successive sweep technique accurately mimic the measured data. In fact, both the simultaneous and proposed successive sweep approaches lead to comparable performances in time and frequency domains. However, the simultaneous sweep approach is significantly more time-consuming and resource intensive, since it involves an extensively large number of combinations. In fact, the simultaneous sweep requires the identification and performance evaluation of $[(N_{\max} - N_{\min} + 1) \times (M_{\max} - M_{\min} + 1)]$ models. Conversely, the maximum number of combinations needed for the proposed successive sweep approach to cover the same range of the nonlinearity order and the memory depth values is $[(N_{\max} - N_{\min} + 1) + (M_{\max} - M_{\min} + 1)]$ combinations. These results clearly illustrate the complexity reduction achieved by using the proposed model dimension estimation technique. This complexity reduction is directly proportional to the sweep ranges of the nonlinearity order and memory depth values. In the considered case, a maximum of 23 simulations is required for the successive sweep approach while 130 simulations are needed for the simultaneous sweep approach. This represents 80% reduction in the computations needed to estimate the model dimension for each signal. The effective computational complexity reduction is even higher when multiple signals are used since the nonlinearity order can be estimated from the measurements with the signal emulating the least memory effects. In the case of the 6 signals considered in this work, a maximum of 73 and 780 simulations are needed to estimate the model dimensions using the successive and simultaneous sweeps algorithms, respectively. Also, it can be observed from the results reported in Table 3 that the model dimensions estimated using the simultaneous sweep approach can be inconsistent with the actual behavior of the DUT.

5. CONCLUSION

In this paper, a novel approach for dimension estimation in memory polynomial based behavioral models is proposed. This technique is based on successively determining the nonlinearity order of the DUT and then its memory depth according to a predefined performance criterion. It was shown that the nonlinearity order can be estimated using either the actual drive signal or a corresponding signal that reduces or ideally cancels the memory effects exhibited by the DUT.

This model dimension estimation algorithm drastically decreases the number of sweep combinations required in the conventional approach, which is based on simultaneously sweeping both the nonlinearity order and the memory depth. The accuracy of this technique was experimentally assessed using a high-power Doherty PA driven by six different WCDMA signals. A large number of simulations were performed using each of these signals to evaluate the appropriate model dimensions, first with the simultaneous sweep method and then with the proposed successive sweep method. The results demonstrated the effectiveness of the proposed algorithm. For a typical 3G wireless power amplifier, the memory depth and the order of nonlinearity range from (0 to 6) and (3 to 12), respectively. In such a case, the proposed approach will require 17 iterations. While in case of the simultaneous sweep method, 70 iterations will be required overall. Also by using the proposed technique, over estimation of the model dimensions is prevented, which reduces the computational complexity of the model while maintaining comparable model accuracy. The reduction of the model dimensions will also minimize the resources' utilization for Field programmable Gate Array (FPGA) implementation.

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