

An Accurate Complexity-Reduced Simplified Volterra Series for RF Power Amplifiers

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Abstract—An accurate complexity-reduced simplified Volterra (ACR-SV) series is introduced for RF power amplifiers (PAs). Based on the conventional simplified Volterra (SV) series, it takes memoryless nonlinearity and memory effect into consideration separately, while connected with a nonlinear memory effect (NME) in order to increase accuracy of the model. The proposed ACR-SV model is assessed using a GaN Class-F PA driven by two modulated signals (a WCDMA 1001 signal and a single carrier 16QAM signal with 40 MHz band width). The experimental results in forward modeling and DPD application demonstrate that the proposed ACR-SV model outperforms the memory polynomial (MP) model, the augmented complexity-reduced generalized memory polynomial (ACR-GMP), and the SV model. Compared with the MP model, the ACR-SV model shows a normalized mean square error (NMSE) improvement of 2.61 dB in forward modeling, average adjacent channel power ratio (ACPR) improvement of 3.7/4.2 dB in the DPD application with less 13% number of model coefficients. In comparison with the ACR-GMP model, the ACR-SV model shows NMSE improvement of 1.39 dB, ACPR improvement of 0.7/0.6 dB with comparable number of model coefficients. In contrast with the SV model, the ACR-SV model achieves similar model accuracy, but reduces approximately 53% of coefficients.

1. INTRODUCTION

Power amplifiers (PAs) are one of the most indispensable components in modern communication system and inherently nonlinear. When PA is operating in a situation, such as driven by multi-carrier envelope varying signals with bandwidth of 20 MHz and more, PA causes serious band distortion as well as spectral regrowth (broadening). To compensate and cancel these nonlinear effects so as to ensure the reliable transmission of information, PA linearization is stringently necessary.

One of the most and cost effective linearization techniques to PA nonlinearity is digital predistortion (DPD) [1, 2], which has many advantages such as high fidelity, efficiency, and easy realization of adaptive processing [3–5]. Moreover, the final purpose of realizing PA linearization digital predistortion needs behavioral modeling precisely, for which Volterra series comes to light. Volterra series can accurately describe the nonlinearity of PA, but it involves a great number of coefficients [6, 7] and is undesirable in practice. Therefore, Volterra-based pruning of the items [8–17] is essential to practical application. The Memory Polynomial (MP) model [13] contains the diagonal terms of Volterra series. The Generalized Memory Polynomial (GMP) [15] combines the MP model with cross items between the signal and lagging and/or leading exponentiated envelope terms. The new simplified Volterra (SV) [16] series combines the GMP model with cross terms between the conjugate signal and lagging and/or leading exponentiated envelope terms. Compared with MP model. The GMP model and SV model are more accurate, while including more multiple coefficients. The ACR-GMP model [17] is a complexity-reduced version of the conventional GMP and obtains comparable performance.

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In this paper, we present an accurate complexity-reduced simplified Volterra series for RF power amplifiers. In application, the proposed model improves the performance of the system sharply. This paper also presents a systematic comparison between the proposed ACR-SV model and different state-of-the-art models, such as the MP model, SV model and ACR-GMP model. Normalized mean square error (NMSE) is considered as an in-band distortion metric, while adjacent channel power ratio (ACPR) is taken to be a spectral regrowth benchmark [18,19]. The comparison results fully illustrate that the ACR-SV model is superior to the other three models in terms of accuracy and complexity. In Section 2, the MP model, SV model, ACR-GMP model and ACR-SV model are introduced. Section 3 presents identification procedure of the ACR-SV model. In Section 4, the forward modeling results and DPD performance assessment are reported. Finally, a conclusion is given in Section 5.

2. MODEL DESCRIPTION

2.1. MP Model

The MP model [13] is a markedly simplified Volterra series, which considers only the diagonal terms of Volterra series, i.e., $m_1 = m_2 = \dots = m_k = m$, it can be represented as

$$y_{MP}(n) = \sum_{\substack{k=1 \\ k\text{-odd}}}^K \sum_{m=0}^M a_{km} x(n-m) |x(n-m)|^{k-1} \quad (1)$$

where $x(n)$ and $y_{MP}(n)$ are the input and output signals of the MP model, respectively. K , M , and a_{km} are the nonlinearity order, memory order, and model coefficients, respectively.

2.2. SV Model

The SV model [16] is an extended version of the GMP model. Based on the GMP model, it adds to a conjugation of input signal with special time delay. Removing the duplicates, the SV model can be written as

$$\begin{aligned} y_{sv}(n) = & \sum_{\substack{k=1 \\ k\text{-odd}}}^{K_a} \sum_{m=0}^{M_a} a_{km} x(n-m) |x(n-m)|^{k-1} \\ & + \sum_{\substack{k=3 \\ k\text{-odd}}}^{K_b} \sum_{m=0}^{M_b} \sum_{l=1}^{L_b} b_{kml} x(n-m) |x(n-m-l)|^{k-1} \\ & + \sum_{\substack{k=3 \\ k\text{-odd}}}^{K_c} \sum_{m=0}^{M_c} \sum_{l=1}^{L_c} c_{kml} x(n-m) |x(n-m+l)|^{k-1} \\ & + \sum_{\substack{k=3 \\ k\text{-odd}}}^{K_d} \sum_{m=0}^{M_d} \sum_{l=1}^{L_d} d_{kml} x^*(n-m) x^2(n-m-l) |x(n-m-l)|^{k-3} \\ & + \sum_{\substack{k=3 \\ k\text{-odd}}}^{K_e} \sum_{m=0}^{M_e} \sum_{l=1}^{L_e} e_{kml} x^*(n-m) x^2(n-m+l) |x(n-m+l)|^{k-3} \end{aligned} \quad (2)$$

where $x(n)$ and $y_{sv}(n)$ are the input and output signals of the SV model, respectively. K_a , M_a , and a_{km} are the nonlinearity order, memory order and coefficients of the aligned terms between signal and its exponentiated envelope, respectively. K_b , M_b , L_b and b_{kml} are the nonlinearity order, memory depth, lagging cross terms index, and coefficients of the signal and lagging exponentiated envelope terms, respectively. K_c , M_c , L_c and c_{kml} are the nonlinearity order, memory depth, leading cross terms index and coefficients of the signal and leading exponentiated envelope terms, respectively. K_d , M_d , L_d

and d_{kml} are the nonlinearity order, memory depth, lagging cross terms index, and coefficients of the conjugate of input signal and lagging exponentiated envelope terms, respectively. K_e , M_e , L_e and e_{kml} are the nonlinearity order, memory depth, leading cross terms index, and coefficients of the conjugate of input signal and leading exponentiated envelope terms, respectively.

2.3. ACR-GMP Model

The ACR-GMP model [17] is a complexity-reduced generalized memory polynomial, while connected with a nonlinear memory (NME) sub-block in parallel in order to improve the model performance, which considers nonlinearity and memory effect, respectively. The NME sub-block is a cascade connection between a conventional memoryless model and a third-order Volterra filter. The output of the NME sub-block is $y_{NME}(n)$ and can be written as

$$u(n) = \sum_{k=1}^{K_a} r_k^{(a)} x(n) |x(n)|^{k-1} \quad (3)$$

$$y_{NME}(n) = \sum_{m=0}^{M_d} d_m |u(n-m)|^2 u(n-m) \quad (4)$$

where $x(n)$ and $u(n)$ are the input and output signals of the conventional memoryless nonlinearity model, and K_a , $r_k^{(a)}$ are the nonlinearity order and memoryless nonlinearity coefficients at the front end. $u(n)$ and $y_{NME}(n)$ are the input and output signals of the third-order Volterra filter, and M_d and d_m are the memory depth and coefficients of the filter at the back end. Then the ACR-GMP model is given by

$$\begin{aligned} y_{ACR-GMP}(n) = & \sum_{\substack{k=1 \\ k-odd}}^{K_a} r_k^{(a)} \sum_{m=0}^{M_a} a_m x(n-m) |x(n-m)|^{k-1} \\ & + \sum_{\substack{k=3 \\ k-odd}}^{K_b} r_k^{(b)} \sum_{m=0}^{M_b} \sum_{l=1}^{L_b} b_{ml} x(n-m) |x(n-m-l)|^{k-1} \\ & + \sum_{\substack{k=3 \\ k-odd}}^{K_c} r_k^{(c)} \sum_{m=0}^{M_c} \sum_{l=1}^{L_c} c_{ml} x(n-m) |x(n-m+l)|^{k-1} \\ & + \sum_{m=0}^{M_d} d_m |u(n-m)|^2 u(n-m) \end{aligned} \quad (5)$$

where $x(n)$ and $y_{ACR-GMP}(n)$ are the input and output signals of the ACR-GMP model, respectively. K_a , M_a , $r_k^{(a)}$ and a_m are the nonlinearity order, memory order, memoryless nonlinearity coefficients, and memory nonlinearity coefficients of the aligned terms between signal and its exponentiated envelope, respectively. K_b , M_b , L_b , $r_k^{(b)}$ and b_{ml} are the nonlinearity order, memory depth, lagging cross terms index, and memoryless nonlinearity coefficients and memory nonlinearity coefficients of the signal and lagging exponentiated envelope terms, respectively. K_c , M_c , L_c , $r_k^{(c)}$ and c_{ml} are the nonlinearity order, memory depth, leading cross terms index, and memoryless nonlinearity coefficients and memory nonlinearity coefficients of the signal and leading exponentiated envelope terms, respectively. M_d and d_m have the same meaning as formula (4).

2.4. ACR-SV Model

Compared with the MP model [13] and GMP model [15], the SV model adds more continuous items to the behavioral modeling of PAs. Therefore, the accuracy of the SV model is considerably high in contrast

to the other two models. However, because of leading in more continuous terms, it has drawback of complexity of the model, i.e., large number of coefficients. The SV model takes the nonlinearity and memory effect into estimation together which leads to that the number of the model coefficients is proportional to products between nonlinearity truncation orders and memory depths. Great values of nonlinearity order and memory depth can result in unacceptable high-complexity. Meanwhile, on account of four more branches than MP model, this kind of situation must be more obvious, i.e., the complexity of the SV model is considerably enormous. Therefore, it is necessary to decrease the complexity of the SV model.

To decrease the complexity of the SV model, its estimation of coefficients about the memoryless nonlinearity and memory effect should be taken into consideration separately. The ACR-SV model is similar to the ACR-GMP model and also adds to the NME sub-block branch to improve model accuracy. The ACR-SV model can be deduced as

$$\begin{aligned}
y_{ACR-SV}(n) = & \sum_{\substack{k=1 \\ k\text{-odd}}}^{K_a} r_k^{(a)} \sum_{m=0}^{M_a} a_m x(n-m) |x(n-m)|^{k-1} \\
& + \sum_{\substack{k=3 \\ k\text{-odd}}}^{K_b} r_k^{(b)} \sum_{m=0}^{M_b} \sum_{l=1}^{L_b} b_{ml} x(n-m) |x(n-m-l)|^{k-1} \\
& + \sum_{\substack{k=3 \\ k\text{-odd}}}^{K_c} r_k^{(c)} \sum_{m=0}^{M_c} \sum_{l=1}^{L_c} c_{ml} x(n-m) |x(n-m+l)|^{k-1} \\
& + \sum_{\substack{k=3 \\ k\text{-odd}}}^{K_d} r_k^{(d)} \sum_{m=0}^{M_d} \sum_{l=1}^{L_d} d_{ml} x^*(n-m) x^2(n-m-l) |x(n-m-l)|^{k-3} \\
& + \sum_{\substack{k=3 \\ k\text{-odd}}}^{K_e} r_k^{(e)} \sum_{m=0}^{M_e} \sum_{l=1}^{L_e} e_{ml} x^*(n-m) x^2(n-m+l) |x(n-m+l)|^{k-3} \\
& + \sum_{m=0}^{M_f} f_m |u(n-m)|^2 u(n-m)
\end{aligned} \tag{6}$$

where $x(n)$ and $y_{ACR-SV}(n)$ are the input and output signals of the ACR-SV model, respectively. K_a , M_a , $r_k^{(a)}$, and a_m are the nonlinearity order, memory order, memoryless nonlinearity coefficients, and memory nonlinearity coefficients of the aligned terms between signal and its exponentiated envelope, respectively. K_b , M_b , L_b , $r_k^{(b)}$ and b_{ml} are the nonlinearity order, memory depth, lagging cross terms index, and memoryless nonlinearity coefficients and memory nonlinearity coefficients of the signal and lagging exponentiated envelope terms, respectively. K_c , M_c , L_c , $r_k^{(c)}$ and c_{ml} are the nonlinearity order, memory depth, leading cross terms index, and memoryless nonlinearity coefficients and memory nonlinearity coefficients of the signal and leading exponentiated envelope terms, respectively. K_d , M_d , L_d , $r_k^{(d)}$ and d_{ml} are the nonlinearity order, memory depth, lagging cross terms index, and memoryless nonlinearity coefficients and memory nonlinearity coefficients of the conjugate of input signal and lagging exponentiated envelope terms, respectively. K_e , M_e , L_e , $r_k^{(e)}$, and e_{ml} are the nonlinearity order, memory depth, leading cross terms index, and memoryless nonlinearity coefficients and memory nonlinearity coefficients of the conjugate of input signal and leading exponentiated envelope terms respectively. M_f and f_m have the same meaning as M_d and d_m mentioned above.

Apparently, the ACR-SV model has approximately equal variables to the SV model, but it realizes the ability of reduction of coefficients, i.e., the ability of reduction of model complexity [20]. The number of the ACR-SV model coefficients is $(K_a + K_b + K_c + K_d + K_e - 3)/2 + M_a + 1 + (M_b + 1)L_b + (M_c + 1)L_c + (M_d + 1)L_d + (M_e + 1)L_e + M_f + 1$.

However, for the behavioral models mentioned above, we consider only odd-order nonlinearities because the even-order kernels can be omitted in a band-limited modulation system [16].

3. MODEL IDENTIFICATION

Since the ACR-SV model includes multiple estimation of coefficients, it is not accurate to estimate coefficients of the model in a single-step least squares (LS) algorithm. It should estimate coefficients of the model separating memoryless nonlinearity and the memory nonlinearity on step-and-repeat operation in order to improve the accuracy of estimation.

Firstly, the vector of the coefficients of memory nonlinearity $a_m, b_{ml}, c_{ml}, d_{ml}, e_{ml}$ can be assumed 1, and f_m may be set to 0 in all its rows, which confirms the consequence of memory nonlinearity expressing as follows

$$\left\{ \begin{array}{l} g_k^{(a)}(n) = \sum_{m=0}^{M_a} a_m x(n-m) |x(n-m)|^{k-1} \\ g_k^{(b)}(n) = \sum_{m=0}^{M_b} \sum_{l=1}^{L_b} b_{ml} x(n-m) |x(n-m-l)|^{k-1} \\ g_k^{(c)}(n) = \sum_{m=0}^{M_c} \sum_{l=1}^{L_c} c_{ml} x(n-m) |x(n-m+l)|^{k-1} \\ g_k^{(d)}(n) = \sum_{m=0}^{M_d} \sum_{l=1}^{L_d} d_{ml} x^*(n-m) x^2(n-m-l) |x(n-m-l)|^{k-3} \\ g_k^{(e)}(n) = \sum_{m=0}^{M_e} \sum_{l=1}^{L_e} e_{ml} x^*(n-m) x^2(n-m+l) |x(n-m+l)|^{k-3} \end{array} \right. \quad (7)$$

On this basis about certain memory nonlinearity, the output waveforms of the ACR-SV model is given by

$$y_{ACR-SV}(n) = \sum_{\substack{k=1 \\ k\text{-odd}}}^{K_a} r_k^{(a)} g_k^{(a)} + \sum_{\substack{k=3 \\ k\text{-odd}}}^{K_b} r_k^{(b)} g_k^{(b)} + \sum_{\substack{k=3 \\ k\text{-odd}}}^{K_c} r_k^{(c)} g_k^{(c)} + \sum_{\substack{k=3 \\ k\text{-odd}}}^{K_d} r_k^{(d)} g_k^{(d)} + \sum_{\substack{k=3 \\ k\text{-odd}}}^{K_e} r_k^{(e)} g_k^{(e)} \quad (8)$$

the coefficients of memoryless nonlinearity can be estimated in a single-step least squares (LS) algorithm. $r_k^{(a)}, r_k^{(b)}, r_k^{(c)}, r_k^{(d)}, r_k^{(e)}$ can be obtained easily. The output of memoryless nonlinearity is given by

$$\left\{ \begin{array}{l} h_a^{(m)}(n) = \sum_{\substack{k=1 \\ k\text{-odd}}}^{K_a} r_k^{(a)} x(n-m) |x(n-m)|^{k-1} \\ h_b^{(ml)}(n) = \sum_{\substack{k=3 \\ k\text{-odd}}}^{K_b} r_k^{(b)} x(n-m) |x(n-m-l)|^{k-1} \\ h_c^{(ml)}(n) = \sum_{\substack{k=3 \\ k\text{-odd}}}^{K_c} r_k^{(c)} x(n-m) |x(n-m+l)|^{k-1} \\ h_d^{(ml)}(n) = \sum_{\substack{k=3 \\ k\text{-odd}}}^{K_d} r_k^{(d)} x^*(n-m) x^2(n-m-l) |x(n-m-l)|^{k-3} \\ h_e^{(ml)}(n) = \sum_{\substack{k=3 \\ k\text{-odd}}}^{K_e} r_k^{(e)} x^*(n-m) x^2(n-m+l) |x(n-m+l)|^{k-3} \\ h_f^{(m)}(n) = |u(n-m)|^2 u(n-m) \\ u(n) = \sum_{k=1}^{K_a} r_k^{(a)} x(n) |x(n)|^{k-1} \end{array} \right. \quad (9)$$

On this basis about certain memory nonlinearity, the output waveforms of the modified SV model is given by

$$\begin{aligned}
 y_{ACR-SV}(n) = & \sum_{m=0}^{M_a} a_m h_a^{(m)}(n) + \sum_{m=0}^{M_b} \sum_{l=1}^{L_b} b_{ml} h_b^{(ml)}(n) + \sum_{m=0}^{M_c} \sum_{l=1}^{L_c} c_{ml} h_c^{(ml)}(n) \\
 & + \sum_{m=0}^{M_d} \sum_{l=1}^{L_d} d_{ml} h_d^{(ml)}(n) + \sum_{m=0}^{M_e} \sum_{l=1}^{L_e} e_{ml} h_e^{(ml)}(n) + \sum_{m=0}^{M_f} f_m h_f^{(m)}(n)
 \end{aligned} \quad (10)$$

Likewise, the coefficients of memory nonlinearity can be estimated in a single-step least squares (LS) algorithm. a_m , b_{ml} , c_{ml} , d_{ml} , e_{ml} and f_m are retrieved. This process proceeds repeatedly to receive more accurate results. In general, it requires only twice processing to give the optimized model coefficients.

4. EXPERIMENTAL VALIDATION

To experimentally demonstrate the proposed ACR-SV model, a high efficiency 20 W GaN Class-F PA ($V_{ds} = 28$ V, $V_{gs} = 5$ V) was tested. This PA was operated at 2.65 GHz and excited by a WCDMA 1001 signal (PAPR = 9.7 dB) and a single carrier 16QAM (PAPR = 8.1 dB) signal with 40 MHz bandwidth, Fig. 1 shows the test bench setup.

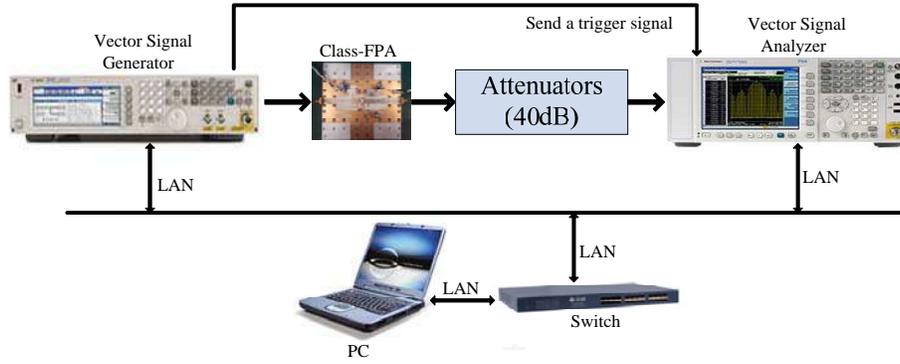


Figure 1. Experiment test bench.

This experiment test bench consists of a GaN Class-F PA, a vector signal generator (N5182A), a vector signal analyzer (N9030A) and a computer. The digital baseband signal was generated in the computer and was downloaded into N5182A, which modulated and up-converted the digital baseband signal that drove the PA with RF input signals. The RF output of the PA was attenuated and then down-converted and demodulated using N9030A. Behavioral modeling and DPD were accomplished by a PC running MATLAB software. In this experiment, 8000 samples of the input and output were used for extracting model coefficients.

4.1. Forward Modeling Results

In the forward modeling, the data of PA output were acquired when PA was operated at about 6 dB output power backoff point, namely, with an output power of PA about 37 dBm. Three aspects, i.e., model dimension, NMSE, and the number of model coefficients, are presented quantitatively in Table 1. The forward modeling results using different behavioral models are summarized in Table 1, which make a good compromise between accuracy and complexity.

As shown in Table 1, compared to the MP model, the proposed ACR-SV model shows a NMSE improvement of 2.61 dB with 13% less number of model coefficients. In comparison with the ACR-GMP model, the proposed ACR-SV model shows a NMSE improvement of 1.39 dB with comparable number

Table 1. Proper comparison of forward modeling results between accuracy and complexity.

Model	Model dimensions	NMSE (dB)	Num. of model coefficients
MP	$(K, M) = (9, 5)$	-41.09	30
SV	$(K_a, M_a) = (7, 4), (K_b, M_b, L_b) = (5, 2, 2),$ $(K_c, M_c, L_c) = (5, 2, 2), (K_d, M_d, L_d) = (3, 2, 2),$ $(K_e, M_e, L_e) = (3, 2, 2)$	-43.83	56
ACR-GMP	$(K_a, M_a) = (7, 3), (K_b, M_b, L_b) = (5, 2, 2),$ $(K_c, M_c, L_c) = (5, 2, 2), M_d = 1$	-42.31	26
ACR-SV	$(K_a, M_a) = (7, 3), (K_b, M_b, L_b) = (5, 1, 1),$ $(K_c, M_c, L_c) = (5, 1, 1), (K_d, M_d, L_d) = (3, 2, 1),$ $(K_e, M_e, L_e) = (3, 2, 1), M_f = 1$	-43.70	26

of model coefficients. In contrast with the SV model, the proposed ACR-SV model shows a NMSE tiny decreasing of 0.13 dB, but reduces almost 53% in the number of coefficients.

To further demonstrate the superiority of the ACR-SV model over the other three models, the relationships of modeling NMSE versus number of coefficients is given in Fig. 2. According to the forward modeling results in terms of NMSE and number of model coefficients, the proposed ACR-SV model uses the least coefficients, but obtains the highest accuracy among these compared models.

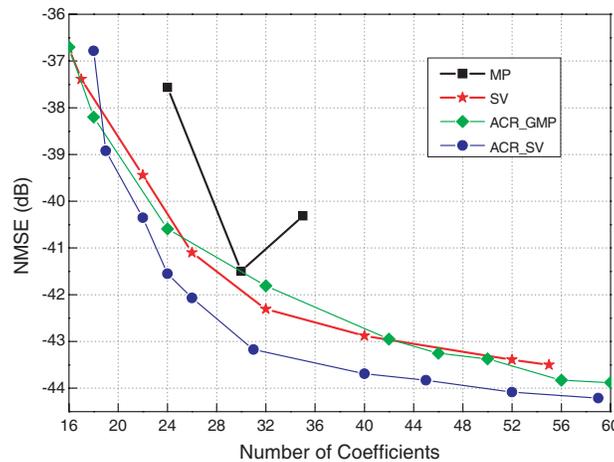


Figure 2. Comparison of four models in terms of the NMSE versus number of coefficients.

4.2. DPD Performance Assessment

Besides the proposed ACR-SV model, the MP, ACR-GMP and SV models were applied to DPD. The model dimensions were set to the proper values highlighted in Table 1. ACPR criterion of outband distortion was used to assess the DPD performance.

The measured ACPRs and number of coefficients for the single carrier 16QAM signal and 4-carrier WCDMA signal are listed in Table 2 and Table 3, respectively. Compared to the MP model, the proposed ACR-SV model shows significant ACPR improvements of 3.7/4.2 dB and 2.4/2.5 dB for the two test signals with 13% less number of model coefficients respectively. In comparison with the ACR-GMP model, the proposed ACR-SV model shows significant ACPR improvements of 0.7/0.6 dB and 0.7/0.4 dB for the two test signals, respectively, with almost identical number of model coefficients. In

Table 2. Comparison of ACPRs for single 16QAM signal.

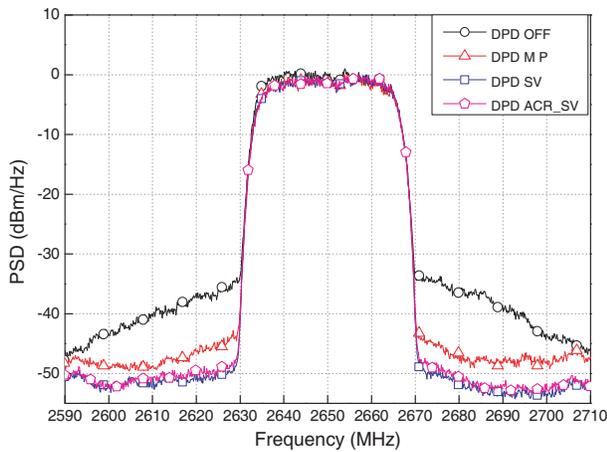
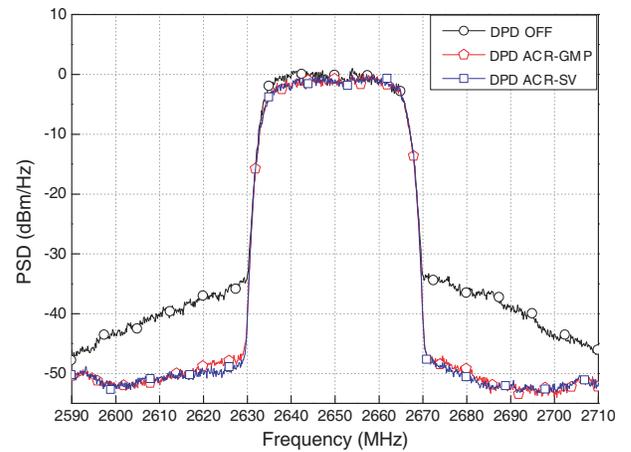
DPD approaches	ACPR of upper band (dBc)	ACPR of lower band (dBc)	Num. of model coefficients
DPD OFF	-37.2	-38.3	/
DPD MP	-45.8	-46.1	30
DPD ACR-GMP	-48.8	-49.7	26
DPD SV	-49.7	-50.8	56
DPD ACR-SV	-49.5	-50.3	26

Table 3. Comparison of ACPRs for WCDMA 1001 signal.

DPD approaches	ACPR of upper band (dBc)	ACPR of lower band (dBc)	Num. of model coefficients
DPD OFF	-41.0	-41.7	/
DPD MP	-48.5	-49.1	30
DPD ACR-GMP	-50.2	-51.2	26
DPD SV	-51.2	-51.7	56
DPD ACR-SV	-50.9	-51.6	26

contrast to the SV model, the proposed ACR-SV model reveals a little ACPR decrease of 0.2/0.5 dB and 0.3/0.1 dB for the two test signals, respectively, but reduces almost 53% in the number of coefficients.

Figure 3 shows the measured spectra at the PA output before and after DPD when using MP, SV and the proposed ACR-SV models for the single band 16QAM signal. Figure 4 shows the measured spectra at the PA output before and after DPD when using ACR-GMP and the proposed ACR-SV models for the single band 16QAM signal. Figure 5 shows the measured spectra at the PA output before and after DPD when using MP, SV and the proposed ACR-SV models for the WCDMA 1001 signal. Figure 6 shows the measured spectra at the PA output before and after DPD when using ACR-GMP and the proposed ACR-SV models for the WCDMA 1001 signal. In terms of NMSE and number of model coefficients, the proposed modified SV model outperforms the other three models.

**Figure 3.** Comparison of the output spectra for single carrier 16QAM signal test, when using MP, SV and ACR-SV DPDS.**Figure 4.** Comparison of the output spectra for single carrier 16QAM signal test, when using ACR-GMP and ACR-SV DPDS.

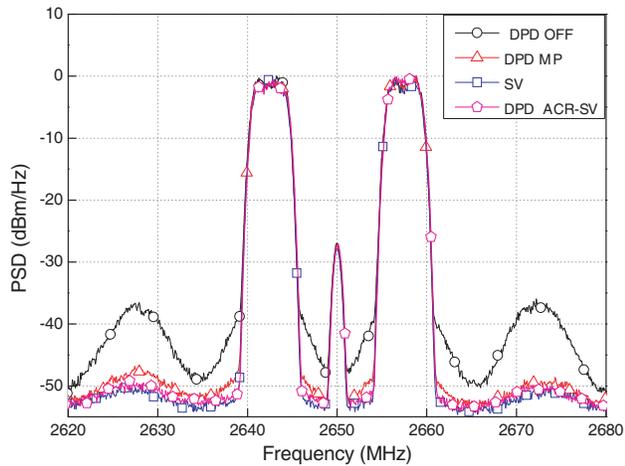


Figure 5. Comparison of the output spectra for WCDMA 1001 signal test, when using MP, SV and ACR-SV DPDS.

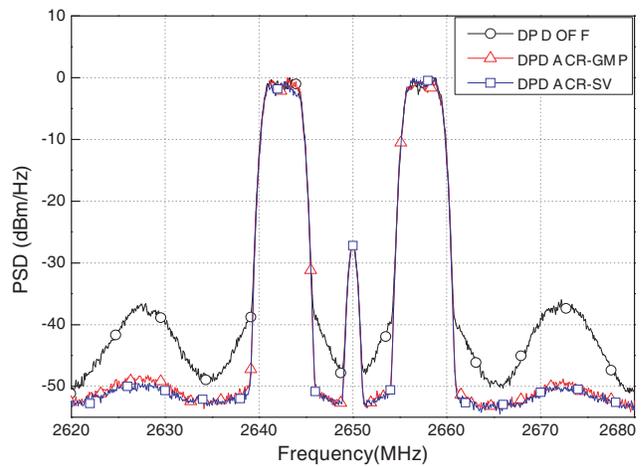


Figure 6. Comparison of the output spectra for WCDMA 1001 signal test, when using ACR-GMP and ACR-SV DPDS.

5. CONCLUSION

In this paper, an accurate complexity-reduced simplified Volterra series model is proposed for behavioral modeling and DPD of wideband RF PAs. It takes estimation of conventional SV model coefficients into memoryless nonlinearity model coefficients and memory nonlinearity model coefficients consideration separately. Through theoretical analysis and practical verification, considering NMSE criterion of inband distortion, ACPR standard of spectral regrowth and number of model coefficients, the results have clearly demonstrate that the ACR-SV model outperforms the other three models.

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