Magnitude-Selective Affine Function Based Digital Predistorter for RF Power Amplifiers in 5G Small-Cell Transmitters

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***Abstract*—To accommodate small-cell deployment in future 5G wireless communications, a magnitude-selective affine function based digital predistortion model for RF power amplifiers is proposed. This model has a very simple model structure and is easy to implement. Experimental results showed, by employing this model, substantial hardware resource reduction can be achieved without sacrificing performance in comparison with the existing models.**

***Index Terms*—5G, affine function, digital predistortion (DPD), power amplifiers (PAs), small cell.**

I. Introduction

Digital predistortion (DPD) has been widely applied to linearization of RF power amplifiers (PAs) to achieve high power efficiency and simultaneously maintain linear signal amplification. In macro base stations, the PAs normally consume several hundred watts of power while, in comparison, the power consumption of DPD units is usually on the order of milliwatts. Although important, the power consumption of DPD has not been a big concern.

In 5G communications, on the one hand, with wider signal bandwidths, the nonlinear behavior of the PAs may become more complicated, calling for more complex DPD models to fulfill the linearity requirement, which can result in increased power consumption in digital circuits. On the other hand, more and more small-cell base stations will be deployed in 5G [1], where the power transmitted by each PA becomes much lower, usually a few watts or lower. To maintain high energy efficiency of the whole system, the power budget for DPD must shrink accordingly. Therefore, in future DPD development, not only the performance is the concern, but the hardware implementation complexity and the related power consumption must also be carefully considered.

The model complexity issue can be tackled in two ways without sacrificing performance. One is to simplify the existing models or develop new but more compact models, while the other is to find more power-efficient hardware implementation strategies. Many efforts have been devoted in both developments. Recently a new behavioral model named decomposed vector rotation (DVR) was proposed in [2]. Experimental results showed that the DVR model can produce excellent performance with a relatively small number of coefficients. This model was derived from a modified form of the canonical piecewise-linear function (CPWL) [3], which is completely different from the conventional Volterra approach. Theoretical analysis has shown that this model is much more flexible and it can be easily implemented in digital hardware with reduced complexity.

In this work, we take the similar concept of piecewise linear function and propose a magnitude-selective affine (MSA) function based DPD model with further simplified hardware implementation.

II. Proposed Model

While developing DPD models, one must obey the "first-zone" constraints defined in [4]: the odd-parity $\tilde{y}[\tilde{x}] = -\tilde{y}[-\tilde{x}]$ and the unitary phase $e^{j1\theta_n}$. The odd parity ensures the output signal is mapped into the odd-order harmonic zones while the unitary phase further restricts the signal in the first-zone. By complying with the two constraints, the model will be physically meaningful and thus does not generate non-physical outputs causing accuracy degradation. Imposing the "first-zone" constraints also provides us with an important guideline in choosing model structures.

A. Review of the DVR Model

The DVR model [2] is given by

$$\begin{aligned}
\tilde{u}(n)|_{DVR} &= \sum_{i=0}^{M} \tilde{a}_i \tilde{x}(n-i) \\
&+ \sum_{k=1}^{K}\sum_{i=0}^{M} \tilde{c}_{ki,1}\big||\tilde{x}(n-i)| - \beta_k\big| e^{j\theta_{n-i}} \\
&+ \sum_{k=1}^{K}\sum_{i=0}^{M} \tilde{c}_{ki,21}\big||\tilde{x}(n-i)| - \beta_k\big| e^{j\theta_{n-i}} |\tilde{x}(n)| \\
&+ \cdots \qquad (1)
\end{aligned}$$

where $\tilde{x}(n)$ and $\tilde{u}(n)$ represents the baseband input and output, respectively. β_k is the threshold value that divides the input range into K partitions. The outer $|\cdot|$ performs the absolute value operation while the inner $|\cdot|$ calculates the magnitude of the input signal. θ_n represents the phase of $\tilde{x}(n)$. M denotes the memory length. $\tilde{a}_i$ and $\tilde{c}_{ki,j}$ are the model coefficients.

It is obvious that the DVR model satisfies the unitary phase condition, as only one θ_n appears in the modeling terms. To meet the odd-parity constraint, DVR combines two basis functions: one is a set of piecewise linear terms $||\tilde{x}(n)| - \beta_k|$, divided by the thresholds β_k, which has even parity; the other is the phase restoration and nonlinear order extension terms $e^{j\theta_n}$, $e^{j\theta_n}|\tilde{x}(n-i)|$, $\tilde{x}(n-i)$ ..., which obeys odd parity. The final model becomes an odd-parity function after multiplying the two parts.

B. Proposed MSA Function Based Model

In DVR model, the even-parity terms are the sum of a number of symmetrical half-line pairs, which can actually be reformulated into one polyline that consists of several segments jointing at threshold values. If we reformat the equation, we can find that this nonlinear operation can be made equivalent to a set of affine functions defined at different magnitude zones, as shown in Fig. 1.

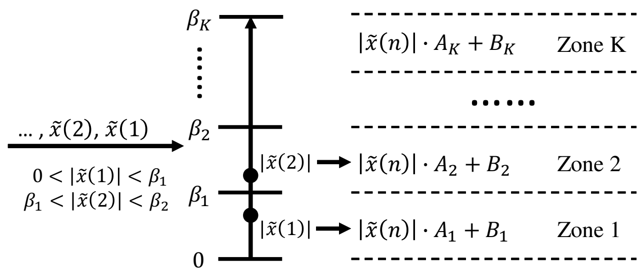

Fig. 1. Magnitude-selective affine function.

Replacing the piecewise absolute value functions with the magnitude-selective affine functions and retaining the nonlinear order extension terms in (1), we can form a new model as following,

$$\begin{aligned}\tilde{u}(n)|_{MSA} &= \sum_{i=0}^{M} \tilde{a}_i \tilde{x}(n-i) \\ &+ \sum_{i=0}^{M} (A_{ki,1}|\tilde{x}(n-i)| + B_{ki,1}) e^{j\theta(n-i)} \\ &+ \sum_{i=0}^{M} (A_{ki,21}|\tilde{x}(n-i)| + B_{ki,21}) e^{j\theta(n-i)} |\tilde{x}(n)| \\ &+ \cdots \\ & \beta_{k-1} < |\tilde{x}(n)| \leq \beta_k. \end{aligned} \quad (2)$$

Instead of applying the same function and model coefficients to all the samples, the new model selects a different set of coefficients for each sample according to its magnitude level. To further explain, take input samples $\tilde{x}(1), \tilde{x}(2) \cdots$, whose values are $0.02 - 0.09j$ and $0.03 + 0.1j$, respectively, as examples. $0.02 - 0.09j$ can be directed into zone 1 while $0.03 + 0.1j$ into zone 2. The nonlinear operation on the samples can then be obtained by $|0.02 - 0.09j| \cdot A_1 + B_1$ and $|0.03 + 0.1j| \cdot A_2 + B_2$, respectively, where A_k and B_k represent gain and offset of the affine function in the given zone.

This process significantly simplifies computational operations and thus dramatically saves hardware resource in DPD implementation. Let's take the 1st-order basis $(A_k\,|\tilde{x}(n)| + B_k)e^{j\theta_n}$ as an example. As depicted in Fig. 2, the input complex signal is decomposed into magnitude and phase using CORDIC algorithm. The obtained magnitude $|\tilde{x}(n)|$ is compared with threshold values to pick the desired gain and offset for the affine function calculation. This piecewise implementation only requires one complex multiplication and one complex addition for all the samples. Phase value is restored by multiplying with $e^{j\theta_n}$. In this way, the MSA model substantially cuts down the computational complexity and hardware cost.

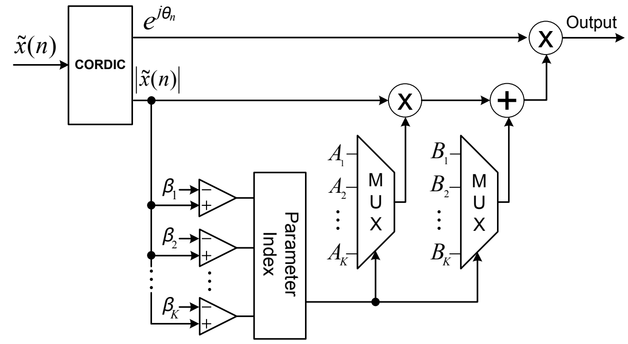

Fig. 2. Hardware implementation illustration.

The proposed magnitude-selective DPD is able to linearize highly nonlinear PAs with simple model structure because different zones only need to compensate for the nonlinearities within certain input power ranges. Based on the operation, we do not need large number of affine functions to reach the desired accuracy. Generally, the number of thresholds can be around 5-20. In addition, the nonlinear terms and cross terms can further enhance the fitting capacity of DPD model. Moreover, time-interleaving structure can also be utilized to relax the digital processing rate requirement in high speed communication systems. This model is thus well suitable for future 5G small cell systems where the power budget for DPD is stringent.

C. Model Extraction

Given high efficiency and flexibility, MSA still retains the linear-in-parameters property, meaning that the general linear system identification methods, e.g. least squares (LS), can be directly applied to extract the parameters. Nevertheless, it is worth mentioning that A_k and B_k only take effect for the specific input zone rather than the entire input range, so formulating the matrix form of (2) can be slightly different.

$$\begin{bmatrix} \tilde{u}(1) \\ \tilde{u}(2) \\ \vdots \\ \tilde{u}(n) \end{bmatrix} = \begin{bmatrix} \tilde{x}(1) & e^{j\theta_1} & 0 & 0 & \cdots & \tilde{x}(1) \\ 0 & 0 & \tilde{x}(2) & e^{j\theta_2} & \cdots & \tilde{x}(2) \\ \vdots & \vdots & \vdots & \vdots & \cdots & \vdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \tilde{x}(n) \end{bmatrix} \begin{bmatrix} A_{10,1} \\ B_{10,1} \\ A_{20,1} \\ B_{20,1} \\ \vdots \\ \tilde{a}_0 \end{bmatrix} \quad (3)$$

or

$$U_{N\times 1} = X_{N\times Q} \cdot C_{Q\times 1} \quad (4)$$

where the subscript N is the total number of input samples and Q represents the number of coefficients. The coefficients are reorganized into one vector C. Constructing matrix X is to allocate the nonlinear terms of input samples to the positions in accordance with the coefficients in the corresponding zone and set irrelevant entries to zeros. For example, $|\tilde{x}(1)|$ lies in zone 1, whose nonlinear terms $|\tilde{x}(1)|e^{j\theta_1} = \tilde{x}(1)$ and $e^{j\theta_1}$ should multiply with $A_{10,1}$ and $B_{10,1}$ respectively. As a result, the rest of matrix elements matching other coefficients are assigned zeros. Finally, LS is operated upon (4) to extract the DPD model coefficients.

III. Measurement Results

To validate the model performance, a test platform was setup, as shown in Fig. 3, which includes PC, baseband board, signal generator, spectrum analyzer and a PA. The PA under test is an in-house designed broadband Doherty power amplifier operating at 2.14 GHz. The excitation input is a 60 MHz 12 carriers UMTS signal with 6.5 dB peak-to-average power ratio (PAPR). Approximately, 16,000 I/Q samples were captured at a sampling rate of 368.64 MSPS. Recorded I/Q input and output samples were time aligned and normalized before training the model. The model extraction and predistorted signal generation were performed in MATLAB. The type-1, 2 and 3 of 2nd-order basis in [2] were selected for both DVR and MSA models. K was set to 7 and M=3, giving 74 and 144 coefficients, respectively.

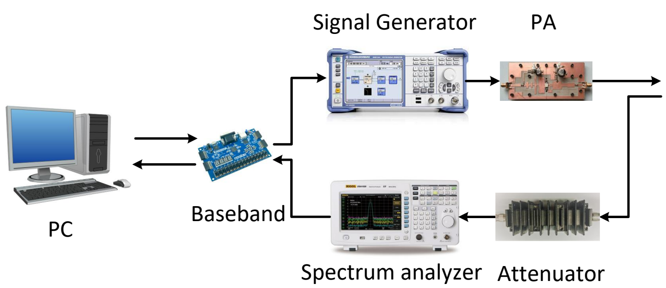

Fig. 3. DPD test bench.

With DPD, the nonlinearities and memory effects were almost completely compensated, as illustrated in Fig. 4. Two models achieved similar performance, that out-of-band distortion has been approximately suppressed to noise floor, which proved the high accuracy of the MSA model.

Prior to the hardware implementation, for comparison, we applied generalized memory polynomial (GMP), DVR, MSA to model PA nonlinear behavior, in order to pre-estimate the computational complexity when achieving more or less the same fitting ability. In terms of GMP model specification, the nonlinear order is 7, the memory length equals 3 and both the lagging and leading steps are set as 3. Normalized mean square errors (NMSE) are displayed in TABLE I, indicating that all three models present similar performance. From the comparison, we can see that GMP uses many more multipliers than DVR and MSA. It is worth mentioning that MSA only requires 1/3 of the multipliers compared to DVR despite the larger number of coefficients.

As GMP was the most costly implementation, here we only compared the hardware complexity between DVR and MSA on FPGA board. Note all the design procedures and bit precisions were the same for DVR and MSA models except

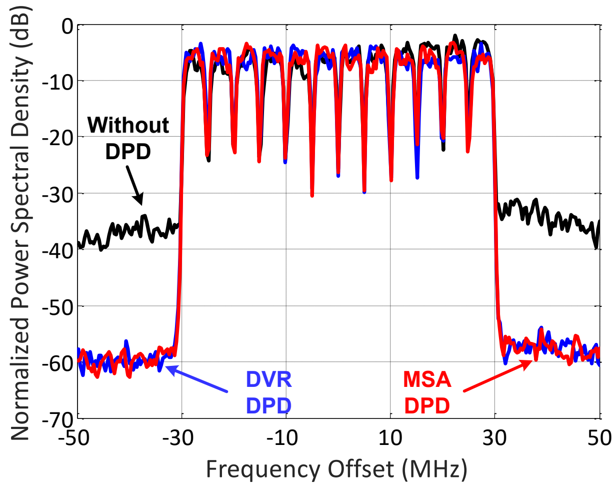

Fig. 4. Signal Spectrum with and without DPD.

the way of constructing the piecewise function. TABLE II illustrated that MSA ended up with a great saving of 60.64% of Flip-flops, 25.67% of Slice LUTs and particularly 85.71% of DSP48 units, comparing to the DVR implementation.

TABLE I
Computational Complexity of GMP, DVR and MSA

	GMP	DVR	MSA
NMSE (dB)	-39.44	-39.59	-39.68
No. of Coeff.	112	74	144
No. of $\otimes$	214	185	65

TABLE II
Hardware Utilization of DVR and MSA

	Flip-flop	Slice LUT	DSP48
DVR	44584	23024	140
MSA	17550	17113	20

IV. Conclusion

A novel DPD model has been proposed for RF PA linearization, with potential application to future wideband and high speed 5G wireless communications. The model performance and low-cost implementation have been verified by experimental tests and FPGA hardware implementation.

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