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Memory Polynomial Based Adaptive Digital Predistorter

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ABSTRACT

Digital predistortion (DPD) is a baseband signal processing technique that corrects for impairments in RF power amplifiers (PAs). These impairments cause out-of-band emissions or spectral regrowth and in-band distortion, which correlate with an increased bit error rate (BER). Wideband signals with a high peak-to-average ratio, are more susceptible to these unwanted effects. So to reduce these impairments, this paper proposes the modeling of the digital predistortion for the power amplifier using GSA algorithm.

***Keywords* -** Adjacent channel power ratio, Digital Predistortion, linearization, Memory polynomial, Power Amplifier.

I. INTRODUCTION

PA are one of the most expensive and most power-consuming components in modern communication systems. They are inherently nonlinear, and when operated near saturation, cause intermodulation products that interfere with adjacent and alternate channels. This interference affects the adjacent channel power ratio (ACPR) and its level is strictly limited by FCC and ETSI regulations [1]. Analog predistortion technology shares similarities with DPD in the sense that both compensate for amplitude-modulation-to-amplitude-modulation (AM-AM) and amplitude-modulation-to-phase-modulation (AM-PM) distortion, intermodulation and PA memory effects, and both employ feedback information to compensate for impairments due to temperature variations and PA aging [2]. Though both approaches share underlying theoretical similarities, the similarities end with their circuit design and system implementations. DPD is one of the commonly used linearizing technique because of its robustness, moderate implementation cost and high accuracy. In DPD linearization technique, as shown in Figure 1, the predistorter (PD) is added in the front of the PA of a nonlinear device with extended nonlinear characteristics just opposite to the nonlinear characteristics of PA [3]. It is used to increase the efficiency of Power Amplifiers, by reducing the distortion caused by Power Amplifiers operating in their non-linear regions. Wireless base stations not employing DPD algorithms typically exhibit low efficiency, and therefore high operational and capital equipment costs.

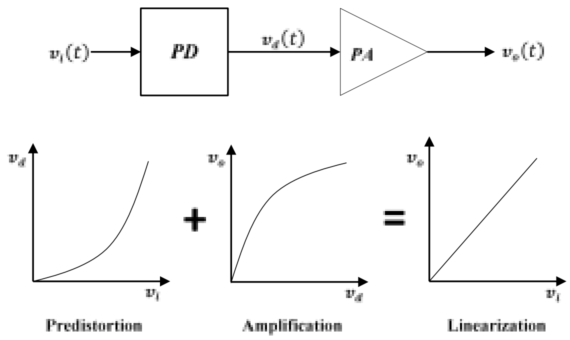

Fig. 1. DPD Process of linearization

This implies that for having linear amplification and thus being compliant with linearity requirements specified in communication standards, significant back-off levels in PA amplification are needed. Back-off amplification results in a power inefficient amplification, moreover when the PA has to handle signals presenting high PAPRs. The use of PA linearizers arises as a recognized solution to deal with this trade-off between linearity and efficiency. The generic configuration can be seen as a simplified decomposition of a general Volterra series function. Among these solutions it is possible to find DPD based on memory polynomials, where the LTI block is usually described by a finite impulse response (FIR) filter [4]. So in this paper GSA algorithm is used to find the coefficients required to model the DPD and PA. Section I is introduction, rest of the paper is as, section II is memory polynomial for modeling the DPD, section III is about GSA algorithm, algorithm steps are discussed in section IV, section V is results for model extraction using GSA algorithm and section VI concludes the paper.

II. MEMORY POLYNOMIAL MODEL FOR DPD

The memory polynomial model used is equivalent to the Parallel Hammerstein model [5-6]. Parallel Hammerstein model can be given as:

$$y(n) = \sum_{k=1}^{K} H_{2k-1}(q)\left|x(n)\right|^{2(k-1)} x(n) \quad (1)$$

The memory polynomial model, however offers a good compromise between generality and ease of parameter estimation and implementation. The memory polynomial model consists of several delay taps and non-linear static functions. The memory polynomial model is a truncation of the general Volterra series, which consists of only the diagonal terms in the Volterra kernels [6]. Thus, the number of parameters is significantly reduced compared to general Volterra series. The model used in present work to develop a polynomial model of a nonlinear system with memory is a truncation of the general Volterra series, which can be shown as [5]:

$$y(n) = \sum_{m=0}^{M}\sum_{k=1}^{K} c_{2k-1,m}\left|x(n-m)\right|^{2(k-1)} x(n-m) \quad (2)$$

Where $x(n)$ is the input complex base band signal, $y(n)$ is the output complex base band signal, $c_{k,q}$ are complex valued parameters, M is the memory depth, K is the order of the polynomial.

In DPD process, one stimulates a non-linear PA with baseband samples and observes the result of that stimulus at the PA output. Then the amplitude-to-amplitude modulation (AM/AM) and amplitude-to-phase modulation (AM/PM) effects of the PA are estimated. These estimated distortions are then removed from the PA by pre-distorting the input stimulus with their inverse equivalents [6].

III. GRAVITATIONAL SEARCH ALGORITHM (GSA)

GSA is the optimization technique, in which agents are considered as objects and their performance is measured by their masses. All these objects attract each other by the gravity force, and this force causes a global movement of all objects towards the objects with heavier masses. Hence, masses cooperate using a direct form of communication, through gravitational force. The heavy masses which correspond to good solutions move more slowly than lighter ones, this guarantees the exploitation step of the algorithm. In GSA, each mass has four specifications: position, inertial mass, active gravitational mass, and passive gravitational mass. The position of the mass corresponds to a solution of the problem, and its gravitational and inertial masses are determined using a fitness function [7].

IV. GSA ALGORITHM STEPS:

Step 1: Initialize of the agents (masses).

Initialize the positions of the N number of agents randomly within the given search interval as below:

$$X_i = x_i^1, x_i^2, \ldots, x_i^d, \ldots, x_i^n \text{ for } i = 1,2,3,\ldots,N \quad (3)$$

Where, x_i^d represents the positions of the i^{th} agent in the d^{th} dimension and N is the space dimension.

Step 2: Fitness evolution and best fitness computation for each agent:

Perform the fitness evolution for all agents at each iteration and also compute the best and worst fitness at each iteration defined as below (for minimization problems):

$$best(t) = \min_{j\in\{1,2,\ldots,N\}} fit_j(t) \quad (4)$$

$$worst(t) = \max_{j\in\{1,2,\ldots,N\}} fit_j(t) \quad (5)$$

Where, $fit_j(t)$ represents the fitness of the j^{th} agent at iteration t, $best(t)$ and $worst(t)$ represents the best and worst fitness at generation t.

Step 3: Compute gravitational constant G:

Compute gravitational constant G at iteration t using the following equation:

$$G(t) = G_o^{\left(-\alpha t/T\right)} \quad (6)$$

In this problem, G_o is set to 100, α is set to 20 and T is the total number of iterations.

Step 4: Calculate the mass of the agents:

Calculate gravitational and inertia masses for each agents at iteration t by the following equations:

$$M_{ai} = M_{pi} = M_{ii} = M_i, \quad i = 1,2,\ldots,N$$

$$m_i(t) = \frac{fit_i(t) - worst_i(t)}{best(t) - worst(t)}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \quad (7)$$

Where, M_{ai} is the active gravitational mass of the i^{th} agent, M_{pi} is the passive gravitational mass of the i^{th} agent, M_{ii} is the inertia mass of the i^{th} agent.

Step 5: Calculate accelerations of the agents:

Compute the acceleration of the i^{th} agents at iteration t as below:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \quad (8)$$

Where, $F_i^d(t)$ is the total force acting on *i*-th agent calculated as:

$$F_i^d(t) = \sum_{j\epsilon Kbest, j\neq i} rand_j F_{ij}^d(t) \tag{9}$$

K_{best} is the set of first K agents with the best fitness value and biggest mass. K_{best} is computed in such a manner that it decreases linearly with time and at last iteration the value of K_{best} becomes 2% of the initial number of agents. $F_{ij}^d(t)$ is the force acting on agent '*i*' from agent '*j*' at d^{th} dimension and t^{th} iteration is computed as below:

$$F_{ij}^d(t) = \frac{G(t)M_{pi}(t)\times M_{aj}(t)}{R_{ij}(t)+\varepsilon}\left(x_j^d(t) - x_i^d(t)\right) \tag{10}$$

Where, $R_{ij}(t)$ is the Euclidian distance between two agents '*i*' and '*j*' at iteration *t* and $G(t)$ is the computed gravitational constant at the same iteration. ε is a small constant

Step 6: Update velocity and positions of the agents:
Compute velocity and the position of the agents at next iteration (t + 1) using the following equations:

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t)$$
$$x_i^d(t) = x_i^d(t) + v_i^d(t+1) \tag{11}$$

Step 7: Repeat Steps 2 to 6 to get maximum limit (iterations).
Return the best fitness computed at final iteration as a global fitness of the problem and the positions of the corresponding agent at specified dimensions as the global solution of that problem [7-8].

V. RESULTS

Model extraction using GSA algorithm

Calculation of proposed model coefficients requires non-linear system identification techniques. In proposed paper, least square (LS) estimation with GSA algorithm has been used to obtain the model coefficients. In order to validate the proposed modeling techniques, a wideband PA data has been taken. The modeled PA was operated with OFDM signal of 2.4GHz frequency and 5 MHz bandwidth. To model the DPD using memory polynomial, the nonlinearity of the model i.e. the order of the polynomial, K was truncated to 7. To consider the memory effects, the memory depth, M was taken as 4. The lower channel values were measured at -10 MHz and -5 MHz, while upper channel values were measured at 5 MHz and10 MHz. To evaluate the DPD model, the coefficients of memory polynomial have been calculated using GSA algorithm. The AM-AM characteristics are very useful to show the behavior of DPD and PA model shown in Fig. 2. The modeled PA and DPD using GSA algorithm are shown in Fig. 3 and 4. The ACPR values for the actual data, modeled PA and modeled DPD are shown in table 1. From these figures and table, the ACPR reduction, accuracy and simplicity of the proposed technique can be easily analyzed.

VI. CONCLUSIONS

Due to its ease of implementation and high ACPR improvement capability, adaptive DPD is one of the widely used approach for PA linearization. So to increase the system efficiency in wideband transmitters and considering the linearity requirement, DPD for PA linearization is proposed. Due to moderate implementation complexity, the proposed approach uses GSA algorithm for extraction of DPD and PA coefficients. Simulations were carried out to evaluate the performance of the models of DPD and PA using the GSA algorithm. Results show that proposed scheme is quite simple and its performance is equally comparable with other techniques.

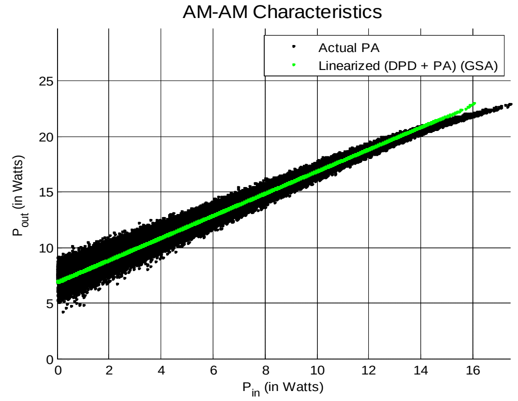

Figure 2: AM-AM characteristics of PA and DPD using GSA algorithm

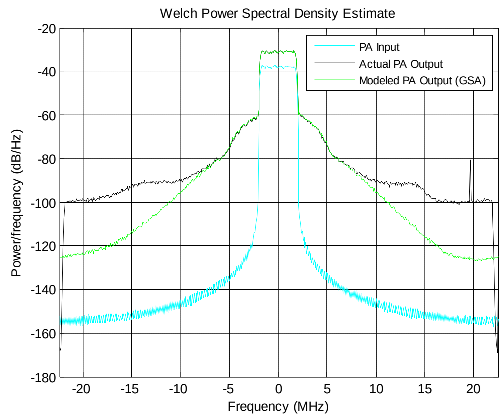

Figure 3: Power spectral density for modeled PA using GSA algorithm

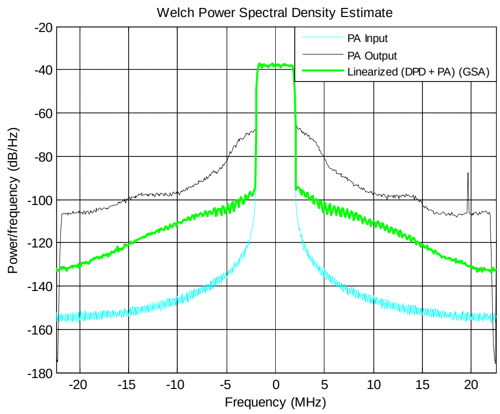

Figure 4: Power spectral density for modeled DPD using GSA algorithm

Table 1. ACPR Measurements for Modeled PA and DPD using GSA algorithm (in dB)

Parameter	Actual	PA Modeled	DPD Modeled
Lower ACPR 2	-59.4759	-80.7511	-58.6616
Lower ACPR 1	-47.0499	--74.2885	-45.5804
Upper ACPR 1	-46.5342	-76.5738	-45.3997
Upper ACPR 2	-60.7407	-81.4125	-55.4727

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