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Global Optimization of Design Parameters of Analog Pre-Distortion Linearizers for RF Power Amplifiers

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Abstract

In this work, we compare a few widely used nature-inspired global optimization algorithms in designing an analog pre-distortion (APD) linearizer to correct a nonlinear GaN power amplifier (PA). A typical dual-branch APD is utilized for this purpose, with the nonlinear branch composed of a driver and nonlinear amplifier, and the linear branch realized by a phase shifter. The relevant design parameters, i.e. driver gain, non-linear amplifier bias resistor, gate voltage, and phase offset, are optimized. Four stochastically based, global optimization algorithms are compared: Particle Swarm (PS), Differential Evolution (DE), advanced Genetic Algorithm (GE), and Random (R) optimization. After performing 10 different and independent optimization trials, each randomly initialized, DE outperforms the other algorithms and converges to the global minimum after about 919 iterations. Using the optimized parameters, the APD+PA characteristics are then used to calculate the APD+PA output spectrum. A reduction of more than 15 dB in spectral regrowth is observed using the optimized APD.

1 Introduction

In modern wireless communication systems, power amplifiers (PAs) play a vital role in generating RF power with high efficiency and linearity. However, RF PAs introduce non-linear behavior that causes signal distortion of the transmitted signal, leading to spectral regrowth and potential interference with nearby channels [1, 2]. Digital and analog pre-distortion (APD and DPD) are two popular techniques useful to reduce PA distortion [1]. DPD operates in the digital domain where the inverted PA characteristics are used to correct the transmitted signal [3]. However, DPD requires the use of a digital baseband, and up- and down-conversion to RF frequencies, added system costs, power consumption, and complexity.

Analog pre-distortion is a well-known technique that can be used to improve PA nonlinearities without needing digital circuitry. With APD, it is possible to achieve higher linearity, efficiency, and lower costs [4]. Similarly to DPD, APD implements with RF circuits the inverted PA characteristics in amplitude and phase over the PA bandwidth. These characteristics can be obtained by directly measuring the PA with typical waveforms, such as two-tones, multi-tones or Gaussian pulses [5]. The APD characteristics are then implemented in the RF hardware which is then connected to the PA input after some amplification to compensate the APD losses, so that the cascade results in an improved linear response.

Various APD topologies are available. For example, single-branch APDs [6, 7, 8] can be implemented with a shunt or series diode. A dual-branch series-diode APD linearizer was investigated in [9, 10] to improve the linearity and efficiency of a K-band PA. A novel tri-branch analog pre-distortion linearizer was introduced that compensates for the gain inflection within a Doherty PA [11].

For designing an APD, a nonlinear analog circuit needs to be designed with the APD gain and phase profile that match the inverted PA gain and phase. The non-linear circuit for the APD can be designed. This can be achieved with CAD software such as Cadence Microwave Office (MWO). With this software, it is possible to optimize the expected APD linearization using cost function by means of optimization algorithms. These optimization algorithms iterate to find the parameters that closely match the targeted APD characteristics.

In this paper, we present a simulation setup for RF CAD software that can be used to study the convergence of different global optimization algorithms, such as Particle Swarm (PS), Differential Evolution (DE), an advanced version of Genetic Algorithm (GA), and Random optimization. The APD is a conventional dual-branch with a compressed amplifier as a non-linearity generator, and a phase delay to optimize the phase response. This non-linear circuit is solved using an optimizer that controls four parameters, and the convergence time of these algorithms is compared for this class of problems.

2 APD Optimization Problem

The compressing characteristics of a GaN PA operating at 1.9 GHz are shown in Figure 1. GaN PAs are typically driven 4-5 dB in compression to achieve high efficiency, but this comes at the expense of a reduced linearity. The PA phase is also non-constant and exhibits 6° positive phase variation. This nonlinear behavior can be corrected with pre-distortion techniques by using the inverted PA gain and phase characteristics.

The APD circuit is shown in Figure 2 and consists of a non-linear branch containing a nonlinear amplifier with the gate resistance R_g and gate voltage V_g as tunable parameters. A driver of tunable gain G_d is introduced in the nonlinear branch to achieve the required compression of the amplifier. To achieve the desired phase rotation, a linear branch with a phase shifter of value ϕ is introduced in the APD. The two branches are fed by a 3-dB input splitter and combined by a 3-dB output combiner (6 dB maximum correction). In this circuit, the input power P_{in} is swept between -40 and 0 dBm at steps of 1 dB in order to induce compression in the nonlinear amplifier. The four parameters of the APD circuit that will be optimized by the algorithm are defined in the following vector:

$$\mathrm{X} = [G_d, V_g, R_g, \phi]. \tag{1}$$

To maximize the match between the APD and the PA inverted characteristics, this paper compares several global optimization techniques. The cost function to be minimized is defined as follows:

$$J(\mathrm{X}) = \sum_{P_{in}=0}^{P_{in,max}} |G_{APD}(P_{in}, \mathrm{X}) - G_{Target}(P_{in})|^2. \tag{2}$$

The APD target nonlinear function corresponds to the inverted PA gain and phase ($-G_{PA}$) and so we have:

$$J(\mathrm{X}) = \sum_{P_{in}=0}^{P_{in,max}} |G_{APD}(P_{in}, \mathrm{X}) + G_{PA}(P_{in})|^2, \tag{3}$$

where the PA complex gain can be expressed as

$$G_{PA}(P_{IN}) = |G_{PA}(P_{in})| \exp[j\angle G_{PA}(P_{in})]. \tag{4}$$

The $|G_{PA}(P_{in})|$ and $\angle G_{PA}(P_{in})$ data are shown in Figure 1. The optimization algorithm will iterate the parameters within their range to find the parameters X_0 providing the global minimum J_0 of the cost function. This optimization is performed in Cadence Microwave Office (MWO) which also integrates circuit solvers such as harmonic balance and electromagnetic simulators. MWO allows the definition of multiple cost functions which, however, have to be expressed in real values. This can be obtained by reformulating the argument of the sum in (3) as:

$$\begin{aligned} &|G_{APD} + G_{PA}|^2 = \\ &= (G_{APD,Real} + G_{PA,Real})^2 + (G_{APD,Imag} + G_{PA,Imag})^2 \end{aligned} \tag{5}$$

In this last equation, the dependency from the parameters has been suppressed for brevity. Therefore, this cost function can be broken into a real and imaginary cost function

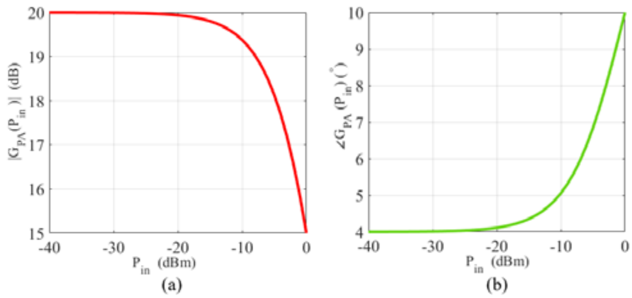


Figure 1. Target PA characteristics. Gain (a) and phase variation (b). These are characteristics of a GaN PA that is driven 5 dB in compression to achieve peak efficiency.

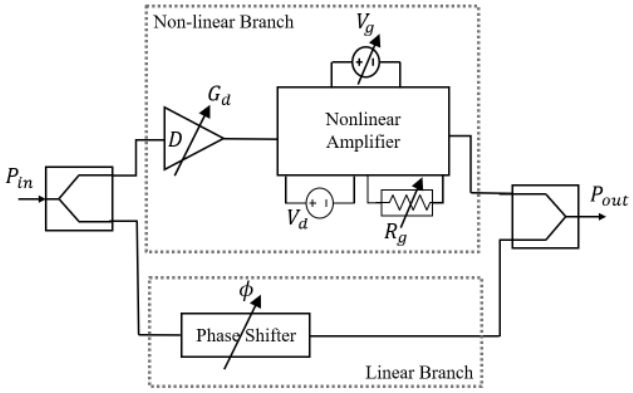


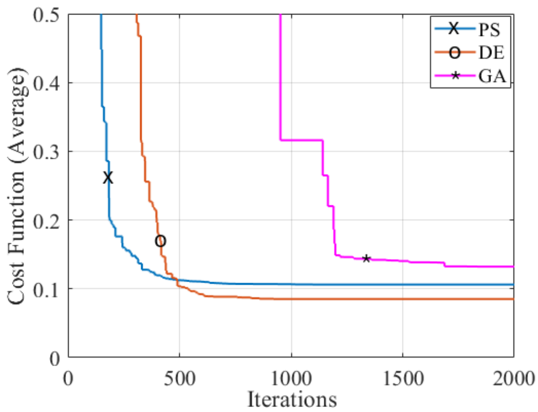
Figure 2. Architecture of the dual-branch APD linearizer used to correct the PA nonlinearities. The values of the driver gain, gate voltage, gate resistor of the amplifier, and phase shifter are optimized.

that can be defined in MWO as follows:

$$\begin{aligned} J_{Real}(\mathrm{X}) &= \sum_{P_{in}=0}^{P_{in,max}} [G_{APD,Real}(P_{in}, \mathrm{X}) + G_{PA,Real}(P_{in})]^2, \\ J_{Imag}(\mathrm{X}) &= \sum_{P_{in}=0}^{P_{in,max}} [G_{APD,Imag}(P_{in}, \mathrm{X}) + G_{PA,Imag}(P_{in})]^2. \end{aligned} \tag{6}$$

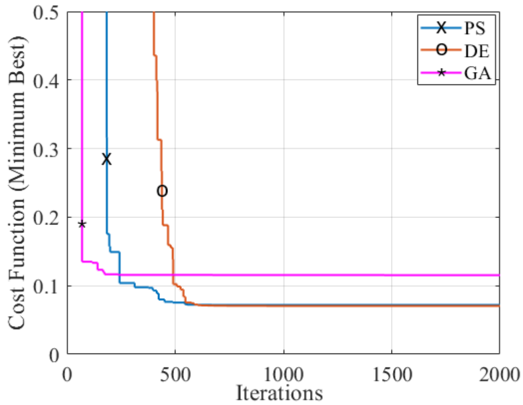
MWO will minimize the sum of these two cost functions as required by the complex cost function of (3). Given the nature of the problem, a global optimization method is required to find the optimal parameters X_0 as the cost function is rather highly nonlinear and multimodal. [12] discusses the advantages and disadvantages of several nature-inspired algorithms. As previously disscused, Particle Swarm (PS), Differential Evolution (DE), Genetic Algorithm (GA), and Random (R) optimization are used here and compared in terms of their convergence rates and ability to find the global minimum, over ten independent trials (“runs"), each involving a random initialization of the parameters X.

To bound the problem within reasonable values, we choose to constrain the parameters in the following ranges: $G_d \in [0, 10]$ (dB), $V_g \in [0.5, 0.8]\,V$, $R_g \in [0, 5000]\,\Omega$, and $\phi \in [0, 90]\,°$. Such ranges are determined by theoretical and physical limitations of the proposed circuit. The initial value of these parameters is initialized randomly according to a uniform probability distribution within the ranges.



(a)

Figure 3. Average cost function variation for the considered algorithms. On average, differential evolution is able to find the lowest cost function.



(b)

Figure 4. Cost function variation achieving the minimum best for the considered algorithms. Differential evolution (DE) achieves the lowest cost function value.

Next, the optimizer ran 10 times until 2000 iterations are completed and results are recorded. For each run, the average cost function between 10 trials and cost function achieving the minimum "best" value are calculated.

Figure 3 shows the average cost function as the number of iterations increases. From this plot, we conclude that the PS and DE present a faster rate of convergence, with the DE achieving the lowest average cost function value of 0.085. Figure 4 shows the cost function variation achieving the minimum as the number of iterations increases. Again, PS and DE present similar performance with the latter resulting in the lowest cost function value of 0.070. From this statistical analysis, between these nature-inspired optimization algorithms, DE is the most suitable optimizer for this class of problems. Among the evolutionary and nature-inspired algorithms, DE has become one of the leading metaheuristics in the class [13]. Finally, Table I reports the performance summary and corresponding cost function for the considered algorithms.

Table I
Performance Summary of the Considered Nature-Inspired Algorithms

Algorithms	J_{AVG}^{FINAL}	$N_{ITER.}^{FINAL}$	J_{MIN}^{FINAL}	N_{ITER}^{FINAL}
Random (R)	0.124	1713	0.107	376
Genetic Algorithm (GA)	0.132	1790	0.115	1469
Particle Swarm (PS)	0.106	1011	0.072	556
Differential Evolution (DE)	**0.085**	**1279**	**0.070**	**919**

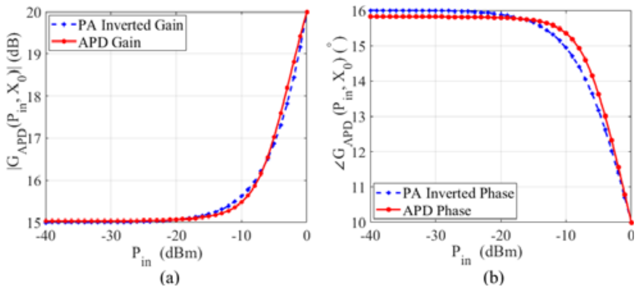


Figure 5. Simulated APD and inverted PA (a) gain and (b) phase profile at 1.9 GHz.

Figure 5 shows the inverted gain and phase profile of the PA at 1.9 GHz that the APD has to implement. A maximum error of +/- 0.3 dB in the gain profile and of -0.7° in the phase profile is observed. When the APD is combined with the RF PA, the combined gain and phase response is shown in Figure 6 (a). The gain presents a variation of +/- 0.3 dB and the phase of -0.7° over the whole input power range.

Figure 6(b) compares the output spectrum of the ideal signal to be transmitted, of the PA-only case, and of the APD+PA case. Although the amplifier boosts the signal, its nonlinearity leads to unwanted distortion, resulting in interference with nearby channels. When the designed APD is added to the PA, the spectral regrowth improves by almost 15 dB thus allowing to operate the PA with higher linearity and efficiency. This means that the APD+PA system has a much cleaner spectrum, with much less unwanted emissions and spectral growth than the PA by itself. This improvement is especially important for today's communication systems, which need high spectral efficiency, low interference, and strict compliance with spectral regulations.

3 Conclusion

In this paper, we presented the result of the optimization of an analog pre-distortion (APD) linearizer for the correction of the gain compression and phase variation introduced by an RF GaN power amplifier (PA). Starting from the PA gain and phase characteristics at 1.9 GHz, a dual-branch APD topology is introduced, and the relevant design parameters are identified. These are the driver gain, the nonlinear amplifier gate resistance, gate voltage, and the phase offset. These four parameters are then bounded within a set range and determined using nature-inspired optimization algorithms. Ten different optimization trials, starting from random parameter initialization are performed, and the average and minimum best of the cost function are recorded. Differential evolution optimization is found to be among the

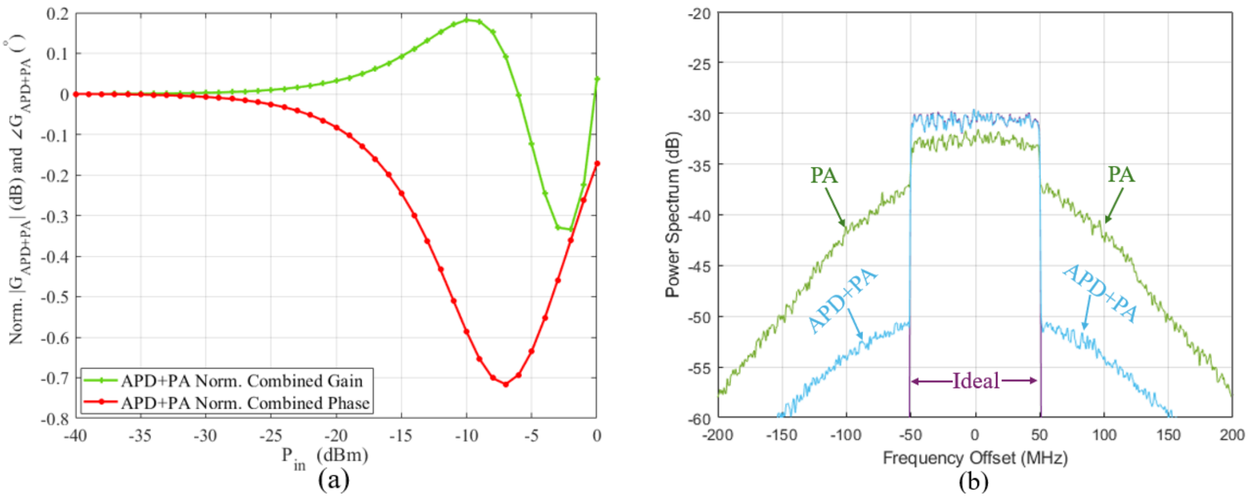


Figure 6. (a): Normalized APD+PA gain/phase variation with input power; (b): Predicted output spectrum for a 100 MHz signal at 1.9 GHz with an ideal PA (purple), with only the PA amplification (green), and with the APD+PA system (blue).

fastest and only algorithm capable of finding the minimum cost function.

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