

Physically Inspired Digital Predistortion for Dual Input Doherty Power Amplifiers and Automatic in-Situ Identification

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Abstract: A novel approach for the linearization of dual input Doherty power amplifier (DPA) is derived by taking inspiration from the operation of the device. A new point of view is evaluated and an automatic identification procedure is developed, reducing the complexity of the predistorter, improving linearity and efficiency at the same time and avoiding the usage of crest factor reduction (CFR). It is also emphasized the importance of a power dependent phase relationship between the inputs of the dual input DPA. A validation of the theory is performed by means of a MATLAB/ADS envelope co-simulation.

1 INTRODUCTION

Modern telecommunication systems are aiming for very high performance demanding high linearity, efficiency and wide bandwidth. A key component of the Base-Station (BS) operation is the power amplifier, which is the major contributor to the whole power consumption of the system. The signals used in order to improve the spectral efficiency have high peak to average power ratio (PAPR) and are decisive in terms of the average efficiency of the whole system. For this reason Doherty Power Amplifiers (DPA) are representing a primary choice for BS applications. DPAs deliver an extended efficiency range and are perfect candidates for amplification of signals with a very high dynamic range. Furthermore, the advances in the design techniques led to new power amplifier (PA) architectures able to deliver high efficiency over a large bandwidth of operation. Class J and JF realizations of the DPA are making use of harmonic terminations to improve the bandwidth. It has already been demonstrated that separating the input branches and driving them separately is of huge benefit in terms of bandwidth and reconfiguration of the power added efficiency (PAE) (Gustafsson, Anderson and Fager, 2012; 2013). Also the concept behind the algorithms for digital pre-distortion (DPD) of dual input DPA were documented (Cahuana et al., 2014), reporting very good

performance and showing the advantages of using this architecture in BSs. The previous research has demonstrated the advantage of driving MAIN and PEAK amplifiers by means of a static splitter, implemented in the digital domain, delivering the optimal combinations of the inputs signals to the PA in order to obtain high efficiency (up to 42%). Despite the improvements, the effect of the phase difference between the two input branches is still not fully characterized yet. In this article we are showing the importance of the power dependent phase correction to be applied at the input of the dual input DPA architecture, and we are presenting a way to automatically identify the optimum combinations of the inputs in-situ. We have reached an average power efficiency of 51%, and we developed a simple physics-inspired algorithm for the pre-distortion that we tested with a 5 MHz LTE signal. The results are demonstrated and validated using envelope simulations in Advanced Design System (ADS).

2 THEORY

In the work of Gustafsson, Anderson and Fager, (2013) it was demonstrated how, the efficiency in power back-off (PBO) of a DPA could be improved and maintained over a wide fractional bandwidth, by introducing the back-off point ϵ_b as a design parameter. All the control parameters of the device

can be expressed as a function of the normalized drive level ε , in particular the output power is expressed as:

$$P_{out}(\varepsilon, f, \theta) = \frac{I_{max_1} RL}{8} \left[\begin{array}{c} \varepsilon^2 + 2\varepsilon \cos\left(\frac{\pi f}{2}\right) \cos(\theta) + \\ k^2 \cos^2\left(\frac{\pi f}{2}\right) \end{array} \right] \quad (1)$$

where I_{max_1} is the maximum current deliverable by the MAIN PA, $\varepsilon_b < \varepsilon < 1$, θ is the phase difference between MAIN and PEAK amplifier input, f is the fractional bandwidth and k is the drive level of the PEAK that sets the efficiency bandwidth of the DPA. In particular, as also demonstrated by the work of Gustafsson, Anderson and Fager (2013), the relationship determining the acceptable values for \bar{f} is:

$$\frac{1 - \varepsilon_b}{1 + \varepsilon_b} = \sin\left(\frac{\pi \bar{f}}{2}\right) \quad (2)$$

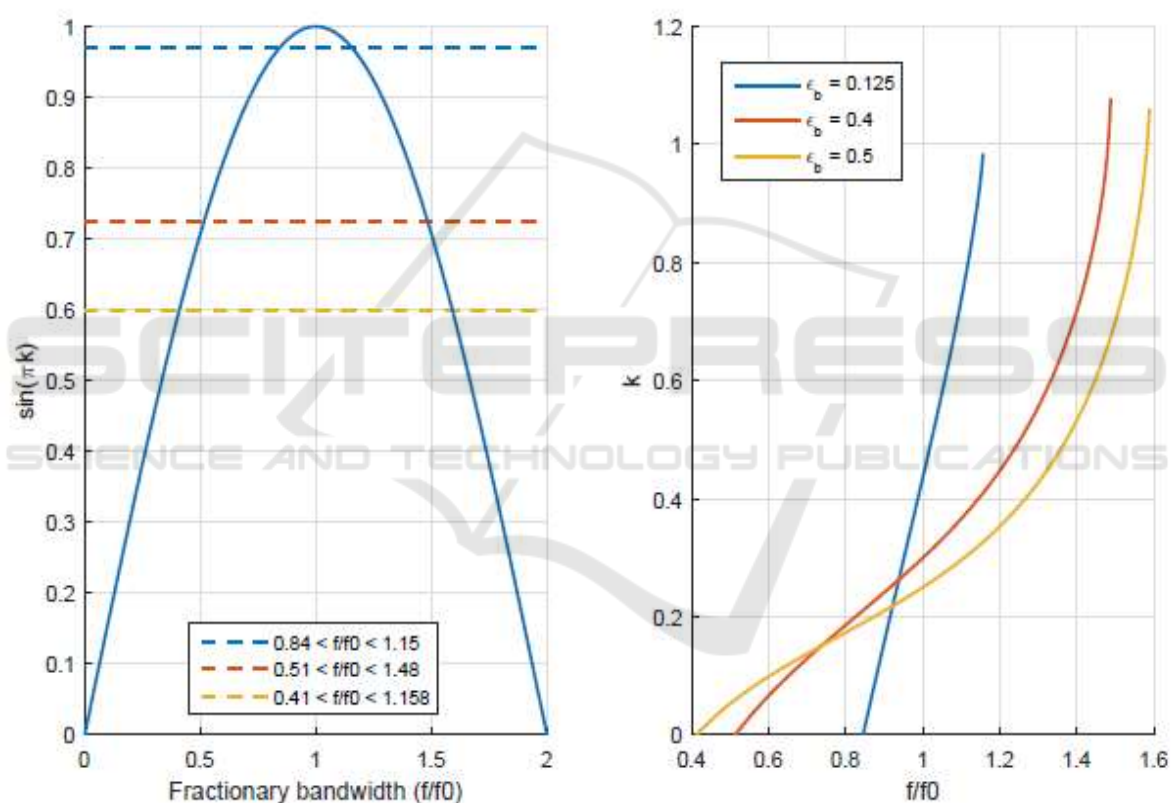


Figure 1: Dependency of the DPA bandwidth on back off poin choice

Figure 1 is graphically showing how the choice of ε_b is decisive for determining the efficiency bandwidth. In addition it was presented a closed formula (Gustafsson, Anderson and Fager, 2013), for the phase relationship between main and peak power amplifier (PA), where the dependency on the fractional bandwidth and the drive level of the PEAK is exploited (3):

$$\theta = \arccos\left(\frac{-k \cos\left(\frac{\pi \bar{f}}{2}\right)}{2\varepsilon}\right) \quad (3)$$

It is clear that the ability to control the input signals of the DPA architecture makes it possible to reach high efficiency both at maximum power and

PBO, causing a active load modulation that assures high performance on an extended frequency range. The theory previously developed by Gustafsson, Anderson and Fager (2013) states that improving the efficiency bandwidth of the DPA architecture leads to a degree of freedom in the reconfiguration of the PA efficiency, depending on the particular frequency where a signal is residing. This is very important for modern BS where we are continuously dealing with multistandard signals and scenarios involving multiband transmission. In Cahuana et al. (2014), this theory was used to implement a digital power splitter to get the maximum power efficiency out of the designed DPA

3 REVISION OF THE IDENTIFICATION PROBLEM

The previous scientific work has opened a lot of possibilities in terms of reconfiguration and bandwidth enlargement. Also if the articles in literature are giving a very good insight of the problem and deliver a solution, it is still unclear how to identify the input combinations in a flexible and automatic way. If we imagine the problem as the identification of a drive function for the DPA, we could depict it as the black box (Figure 2):

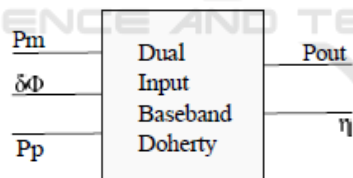


Figure 2: Block scheme for the identification of a drive function.

where P_m , P_p and $\delta\phi$ are respectively the values of the input powers for MAIN and PEAK amplifier, and the phase relationship between them. At the output of the model we have the power and the power added efficiency. Seen in this way, the identification of a single drive function can be exploited as a multidimensional optimization problem. Specifically if we could try all the possible triplets (P_m , P_p , $\delta\phi$), we would end up discovering that there is a theoretically infinite number of combinations leading to the same output power. The challenge relies in identifying the triplets maximizing the efficiency for a specific power level and frequency. In order to do so performed an analysis on the model of a dual input DPA with 300

MHz of bandwidth (700 to 1000 MHz) and a maximum output power of 100 W. A set of measurements in ADS was obtained by means of harmonic balance (HB) simulations, performing a large power sweep over the possible combinations of the input parameters at four frequency points. The results of the simulations at 900 MHz are shown in Figure 3:

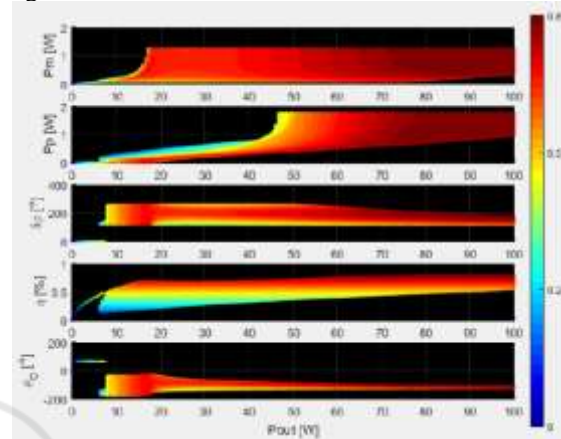


Figure 3: Multidimensional identification dataset for drive function.

where η is the power added efficiency and ϕ_0 is the output absolute phase of the PA. The color is coding the information about the efficiency value assumed by a specific point, with a resolution of about 2%. Analyzing the results in figure 3 it becomes obvious how several combinations of the inputs lead to the same output power but not to the maximum efficiency. This appears much more evident in the middle power region. The image was generated by separating the data into bins in order to reduce dimensionality of the dataset, which is otherwise composed of more than 90.000.000.000 points. Despite the separation into bins the data are quite dense, so in order to better appreciate the magnitude of the problem we should zoom in. Figure 4 presents a closer view of the data. Using different triplets we could generate 38 W at the output of the PA, but in a very small range around it (4 mW) we could drop the efficiency to 30% or less by choosing a suboptimal triplet.



Figure 4: Detail of the characterization space for P_m .

In (Cao et al, 2012) an algorithm for the DPD of dual input power amplifiers was presented. From the

developed theory, it turns out that the knowledge of an optimized signal for the peak power amplifier is necessary, together with the desired RF output signal, in order to determine the shape of the predistorter signal of the main PA. This technique has a higher complexity than the classic approach, but because the nonlinear order used was low it was still considered acceptable. This algorithm shows a good linearization performance and also tries to optimize the efficiency, but it seems that the compromise between the two goals avoids obtaining a very good efficiency in PBO.

4 NOVEL LINEARIZATION APPROACH

We can improve the identification of the digital static splitter by optimizing it for both efficiency and linearity. Below the compression point the response of the system is depending only on the behavior of the MAIN PA. Defining the drive function in the power domain, we can build a model for the predistorter of the MAIN branch with a piecewise lookup table (LUT).

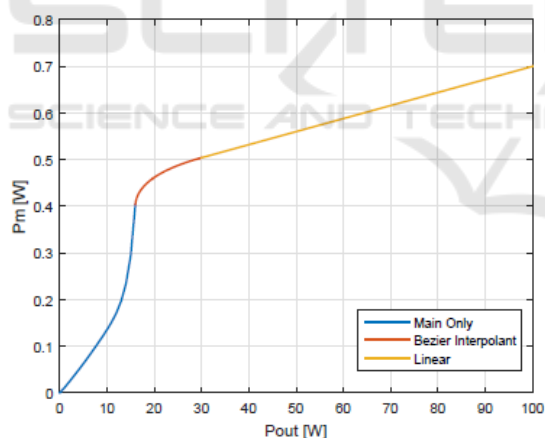


Figure 5: Example of MAIN drive function.

Referring to Figure 5 we have three different sections of the curve. The first one is obtained by turning the PEAK PA off and sending a power ramp to the MAIN PA. We can determine its saturation power and choose the back-off point. Interestingly we are free to reconfigure the power efficiency of the dual input DPA by moving the back-off point. There is a trade off between linearity and efficiency when choosing the back-off point. By deciding the compression point of the MAIN PA we can allow a

certain amount of nonlinear effects included in the system. The drawback observed is a decrease of the back-off efficiency. The third part of the curve is linear because we don't want to generate nonlinear effects by predistorting.

The two curves could be directly blended but this would generate problems in terms of bandwidth expansion of the input signal. The knee between the two curves is a discontinuity in the first order derivative of the function and is responsible for the generation of very high frequency components in the spectrum. The bandwidth expansion generates issues in the signal reconstruction path because the DAC has a bandwidth limited by its sampling frequency which is not infinite. By using a Bezier interpolant (Ping and Guozhao, 2011) to connect the two curves, we are reducing the nonlinear effects of the curve and improving the spectral efficiency by introducing G2 continuity at the blending points. By defining the behavior of the MAIN PA predistorter we reduce the dimensionality of the identification problem and we detect the right value of output power for the DPA in that point. Since we are trying to linearize the device, we would like to have an output characteristic which is linear in the amplitude and possibly constant in phase. Using the information about the output phase at the back-off point, we can set a target for the algorithm performing the identification of the drive functions. As in Cao et al. (2012), we can define a target output power (equally spaced power points) with the condition of constant output phase joined with a LUT of powers to drive the MAIN PA. The first main difference with the work of Ca, is that we are not introducing any DPD mathematical model, we are instead using a certain number of supports (for instance 200) to extract the LUTs used later as references to interpolate between the values. LUTs can be considered less performing, especially in terms of bandwidth expansion, when compared to polynomials, but it was already demonstrated (Barradas et al., 2014) that they can be reformulated in order to be as efficient as the polynomial model. In order to identify the missing predistorter functions, an intelligent algorithm can be applied. We need to define a cost function and minimize it in order to find the value of the PEAK and phase predistorted signals. A good candidate for such function is the pure error vector module EVM (not the classic EVM used for constellations), which can be easily calculated as:

$$EVM = \frac{|S_r - S_i|}{|S_r|} \quad (4)$$

which is expressing the ratio between the error vector and the original vector. The EVM also accounts for the output phase, so by minimizing it we are able to find the correctly aligned output vector with the wanted power and efficiency. It should be emphasized that the minimization problem uses a mono dimensional cost function. The efficiency optimization is performed by choosing the target output phase that we want to maintain at the PA output. Gradient based algorithms such as the ones used to train the classic DPD models could be used to minimize a specific cost function, but they have experimentally exhibited slow convergence on this kind of problem. In addition they could converge to global minima, preventing the discovery of an absolute minimum. Particle Swarm Optimization (Kennedy et al., 1995) is a very attractive algorithm for this sort of application because it is simple and allows control over the power range swept at the input of the DPA. PSO is really useful in a real application in order to avoid damaging the devices due to wrong drive levels. In the literature there are already documented uses of PSO in the field of DPD (Abdelhafiz et al., 2013) for the computation of the coefficients of DPD models. Here we would use it for identifying the optimum triplets directly. The idea behind PSO is very simple, a single particle is described by a set of parameters:

- Position (X): described by the decision variables
- Velocity (V): velocity of the particle during its motion, defines also the direction of search
- Local Best (L): local best met by the particle, updated each time the local best is improved during the search
- Global Best (G): global best found by the whole swarm, this information is shared between all the particles

Each particle is moving in the 2-dimensional space updating its speed according to the social interactions with the rest of the swarm. The formulas to update the velocity and position are expressed as in 5 and 6.

$$\begin{aligned}
 V^{n,d} &= \chi V^{n,d} + c_1 \text{rand}(\cdot)(L^{(n,d)} - \\
 X^{(n,d)} &\oplus c_2 \text{rand}(\cdot)(G^{(n,d)} - \\
 &X^{(n,d)})
 \end{aligned} \quad (5)$$

$$X^{n,d} = X^{n,d} + V^{n,d} \quad (6)$$

Table 1: PSO algorithm

Algorithm 1 PSO

- 1: Initialize a population of particles with random values positions and velocities from D dimensions in the search space
 - 2: Return the global minimum G and the values of the input variables generating it
 - 3: **while** Termination condition not reached **do**
 - 4: **for** Each particle i **do**
 - 5: Adapt velocity of the particle using Equation 5
 - 6: Update the position of the particle using Equation 6
 - 7: Evaluate the fitness $f(\vec{X}_i)$
 - 8: **if** $f(\vec{X}_i) < f(\vec{P}_i)$ **then**
 - 9: $\vec{P}_i \leftarrow \vec{X}_i$
 - 10: **if** $f(\vec{X}_i) < f(\vec{P}_g)$ **then**
 - 11: $\vec{P}_g \leftarrow \vec{X}_i$
-

The coefficients appearing in the equation of the velocity are controlling the "memory" of the particles to lead them towards the best solution that has been found so far. Coefficient c_1 is controlling the tendency of the particle to search in the direction of its own best found solution, while c_2 manages the

social interaction of the particle with the rest of the swarm members to let its position drift towards the global best found by the whole swarm. The flow of the optimization algorithm 1 is very simple to implement and can be adapted to a large range of problems by performing a proper sensitivity study of

the parameters. To make sure that the particle swarm optimizer does not stop if no convergence is met, a maximum number of iterations can be established. This also sets the speed of the algorithm in the worst case, when no optimum is found or when the cost function does not reach the expected precision

5 APPLICATION OF PSO TO STATIC DRIVE FUNCTION IDENTIFICATION

In our approach, the PSO algorithm described above was adapted to the problem of the identification of a single static drive function: Position X is a bi-dimensional vector made of P_p (expressed in W) and $\delta\Phi$ (expressed in degrees); a vector for the target output power is generated by defining 50 equally spaced values; the target output phase is established by using the procedure explained in the previous section.

6 SIMULATION SETUP

In order to prove the concept, a co-simulation MATLAB/ADS was performed. Signal generation, baseband signal processing and analysis of the results were performed in MATLAB while the whole physical part of the simulation was performed by ADS which was configured to perform circuit envelop simulation. The workflow represented in Figure 6 starts with a MATLAB script generating the drive function for the MAIN PA with only 50 points, defining the linear power target points and identifying the back-off point in the same way described in the previous sections.

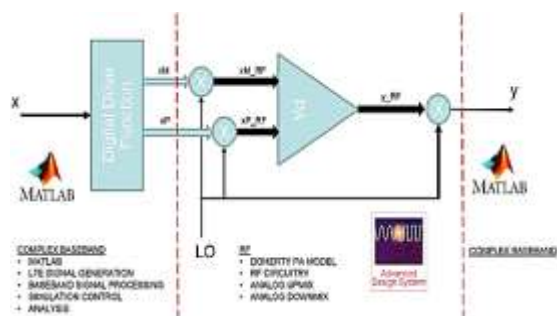


Figure 6: Simulation setup interfacing MATLAB and ADS.

When the algorithm reaches the back-off point it reads the output phase of the PA and starts the particle swarm optimizer to sequentially compute the right pre-distorted phase and power for the peak PA. Since we want to characterize the static correction for the DPA, in MATLAB we are generating constant power points of a duration which avoids memory effects to be sensed at the output. It was experimentally seen that the memory effects of the PA model are visible just up to 300 ns. For this reason we have set the duration of the power pulses to 1 μ s. The convergence of PSO is improved by using more particles, but this also means a bigger number of evaluations and slower results. We used $N = 20$ particles as a good compromise between the simulation time and the precision of the results. To limit the maximum duration of the simulation we have set the number of maximum iterations to 50. The whole simulation takes about:

$$T_{sim_{max}} = N_{particles} * N_{targets} * N_{max-iterations} * T_{cycle} \quad (7)$$

Unfortunately such simulation is time consuming because of the calls to ADS made from MATLAB. The simulation for one point takes about two seconds, so the whole duration, in the worst case, is about 27 hours. The solution is found after less than 10 iterations, so the simulation can be completed in 2 to 5 hours. We expect that by performing the measurement in-situ using an FPGA system, the time to measure each point can be reduced to the limits of memory effects, resulting in a complete identification of the drive function in 15 ms. This process can be applied around several carrier frequencies, creating a raster of drive functions to obtain a wideband model. This workflow generates a LUT, which is used to evaluate the results by running a simulation with an LTE signal. Results are shown in the next section.

7 RESULTS

We have simulated the identification of the drive function by setting the carrier frequency to 900 MHz. The identified drive function is shown in Figure 7.

Looking at the phase relation between MAIN and PEAK driving signals, we noticed that phase is ranging from 200 degrees, at low output power, to 166 degrees at the maximum power. There are 340

of total phase variation, which is not a negligible quantity to account for. This shows the importance of the relationship between P_p and $\delta\phi$, which is why we should choose dual input DPAs for BS operation. By correctly tweaking P_p we select a specific phase relationship, at the input of the structure, maximizing linearity and efficiency for a specific carrier frequency.

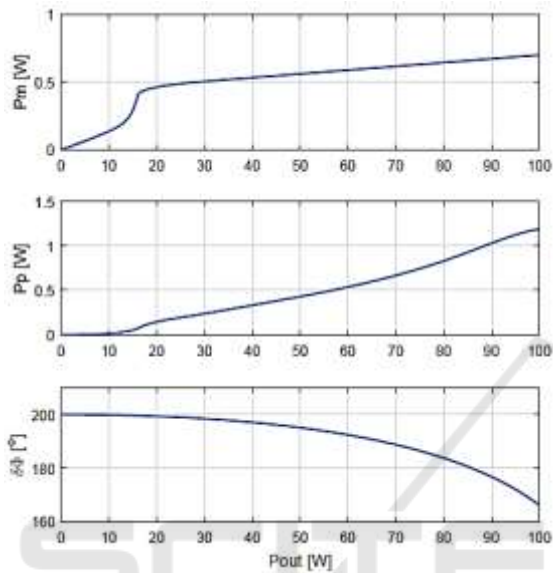


Figure 7: Drive function for the DPA at 900 MHz.

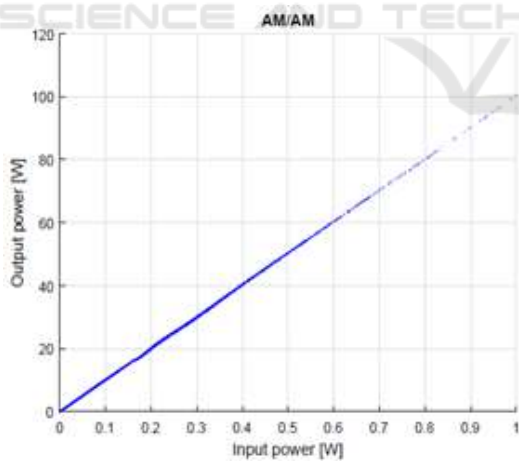


Figure 8: Amplitude Input Output characteristic of DPA + DF.

Looking at the phase relation between MAIN and PEAK driving signals, we noticed that phase is ranging from 200 degrees, at low output power, to 166 degrees at the maximum power. There are 34 degrees of total phase variation, which is not a negligible

quantity to account for. This shows the importance of the relationship between P_p and $\delta\phi$, which is why we should choose dual input DPAs for BS operation. By correctly tweaking P_p we select a specific phase relationship, at the input of the structure, maximizing linearity and efficiency for a specific carrier frequency.

Using the drive function to pre-distort the DPA driven by a 5 MHz LTE signal with a 10 dB PAPR (no CFR was applied), we obtained a linear output characteristic (Figure 8), where the dispersion around the curve is due to the memory of the device.

As we can see in Figure 9, the whole system still shows a non-linear phase characteristic

This is due to the fact that the identification process is done on the two separated inputs of the DPA. When applying a dynamic signal, the splitter does not account for the phase difference between the input of the DF and the output of the DPA.

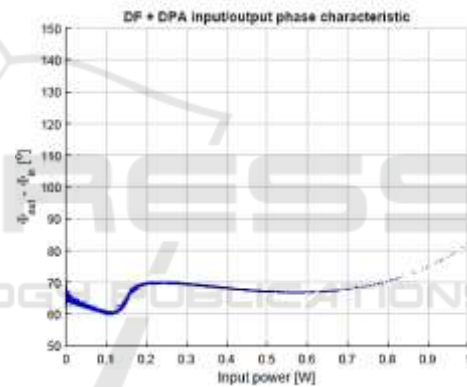


Figure 9: Phase characteristic of DPA + DF

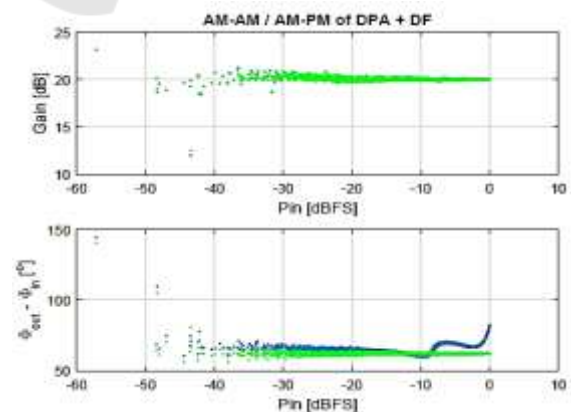


Figure 10: AM-AM and AM-PM characteristic of DF + DPA after static phase correction

Such phase difference can be statically corrected by a common identification technique. We can see the effect of the phase linearization in Figure 10.

After applying the static phase correction (SPC) we obtained a drastic improvement of the ACPR, from 30 to 54 dBc (Figure 11) and an average power added efficiency of 51.1%.

This represents a very good result, considering that no CFR was applied to the input signal.

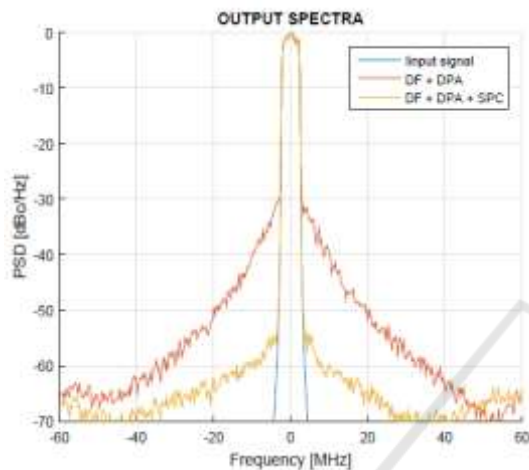


Figure 11: Resulting output spectra

8 CONCLUSIONS

In this article a novel approach for the linearization of dual input DPAs was presented.

We showed how, taking inspiration from the device operation, flexible reconfiguration of the efficiency can be obtained by means of a digital drive function. In addition to that, we developed an automatic identification procedure eligible for FPGA implementation, due to its simplicity.

The algorithm performs an optimization of the input signals for the device and avoids a multi-object approach delivering maximum efficiency by keeping the linearity conditions at its output.

The procedure was validated by making use of a MATLAB/ADS cosimulation environment and testing the workflow on a 5 MHz LTE signal with a 10 dB PAPR. Results have demonstrated that very good performance can be reached without introducing CFR in the transmit chain.

Therefore this opens a huge number of possibilities to adapt the performance to the signal's probability density function and to future multiband approaches for the linearization of this architecture.

Combined together, the identification of several drive functions at different frequencies and, novel techniques for the detection of the instantaneous frequency of non-stationary signals, can lead to a new wideband approach to the DPD.

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