Digital Predistortion Challenges in the Context of Software Defined Transmitters

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Abstract

This paper discusses the challenges associated with the application of the digital predistortion (DPD) technique in the context of software defined transmitters. Given the importance of the DPD technique for compensating for the sources of distortions, and consequently improving the tradeoff between the linearity and the power efficiency, this paper examines the sensitivity of two DPD schemes, namely Memory Polynomial and the Two Hidden Layer Artificial Neural Networks, to the frequent changes in the characteristics (such as the modulation bandwidth, probability density function, peak-to-average power ratio) of the software-defined transmitters' input signals.

1. Introduction

The diversity in the wireless networks' standards and their multiple possible configurations pose stringent requirements on the design of radio transceivers. This yielded an increasing demand for new radio systems and circuits topologies that are inherently multi-mode, and that maintain performance in a wide range of frequencies with programmable channel bandwidth and modulation characteristics. These later are commonly called Software Defined Radio (SDR) [1]. Several approaches have been tried to enable software-enabled transceivers - and more particularly software-defined transmitters (SDT) - through new architectures and circuit techniques. Figure 1 depicts one of those techniques which employ fully analog/RF methodology using a conventional frequency agile direct conversion transmitter followed by a broadband or multi-band power amplifier (PA). Furthermore, at the radio system level, emerging wireless networks are raising their requirements for the PA, with the goal of meeting strict linearity specifications and high power efficiency. To that end, the efficiency enhancement techniques have often been combined with a linearization technique such as digital predistortion (DPD). In the literature, researchers have seized on the capability of artificial neural networks (ANN) [2], Volterra series [3], and its derivations, to propose several DPD schemes with proven linearization capability. With the growing demand in signal bandwidth, these DPD schemes evolved from simple memoryless to more advanced schemes such as memory polynomials (MP) [4], as well as other non-polynomial models using several arrangements of ANNs. Yet, current DPD schemes have often been evaluated in a context of static radio communication scenario. In other words, the linearization capability of these DPD schemes is generally tested using single mode signals. However, SDR technology calls for adaptive transmitters capable of maintaining stringent specifications under multimode operating conditions. Hence, it is essential to examine the capacity of current DPDs to maintain the linearization performance when the signal characteristics are changed without requiring a new set of parameters in each scenario. This aptness is hereafter referred to as the DPD "Generality".

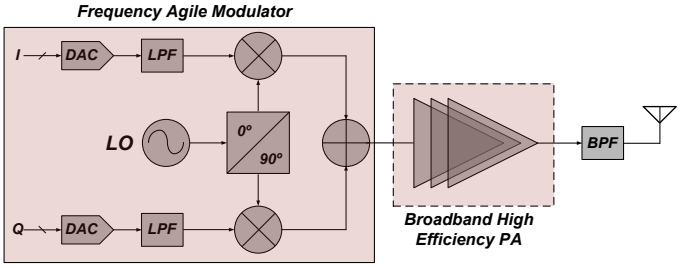

Figure 1 – Multi-standard direct conversion transmitter

This paper will start with the description of two DPD schemes, namely the popular Memory Polynomial (MP) and the recently-introduced two-hidden layer artificial neural networks (2HLANN). An experimental study of the generality of these mentioned DPD when the Probability Density Function (PDF), the Peak to Average Power Ratio (PAPR) and the modulation bandwidth in SDTs are changed will be described.

2. Digital Predistortion of the RF Power Amplifier

This section starts with the description of the MP and 2HLANN DPDs, which have been chosen as representatives of two categories of DPDs, namely physically inspired and unsighted "black box" DPDs.

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2.1. Complexity Reduced Memory Polynomial DPD

The development of the MP-DPD has been mainly motivated by the need to reduce Volterra's model complexity while maintaining its modeling capability, by eliminating the cross-terms and retaining only the dominant distortion terms - i.e., its diagonal kernels. Nevertheless, it has been identified that even the MP-DPD also suffers from the redundant parameters, and the real challenge is to single those out. In fact, the complexity of the DPD scheme has been an essential criterion in determining its implementation feasibility, as it greatly affects its synthesis' complexity and numerical stability, and its execution burden. In the following the similarity between the MP and the Parallel-Hammerstein (PH) will be exploited to devise a systematic approach for their complexity reduction. In fact, unlike the MP, the PH structure splits its overall nonlinearity behavior into different terms based on their order of nonlinearity, thereby assigning a separate Finite Impulse Response (FIR) filter for each nonlinear order, as shown in figure 2. Hence, instead of the usual iterative trial and error approach, the reduction of the number of coefficients can be reliably done with only the first set of measurements based on the filter characteristics of each memoryless nonlinearity level. A detailed description of the PH formulation and the corresponding complexity reduction approach is given in [5].

Starting from the coefficients of the PH scheme, constructed with an order of nonlinearity of N (chosen hereafter to be equal to 9) and a memory order of M (chosen hereafter to be equal to 10), the different filters' coefficients, corresponding to the nonlinearity orders of 1, 3, ..N, are visualized. These coefficients tend to converge to a certain range that is much lower than the first tap, whereas the rate of change between taps becomes minimal. This implies that the signal samples corresponding to those memory levels do not affect the output of the model, or equivalently the corresponding DPD. Therefore, eliminating those taps would reduce the complexity of the model without compromising its accuracy and linearization efficiency. As a result, the FIR lengths can be determined by examining the last significant filter tap on the visualization, and cutting out the taps after the change in amplitude trend—in other words, after the drop in tap amplitudes. It is worth mentioning that, as the first tap of each filter corresponds to the purely nonlinear, memoryless response, its amplitude is much higher compared with the rest of the taps that correspond to the perturbations of smaller amplitude associated with memory effects, thus when comparing the amplitude trend of the FIR, the first tap is skipped.When applied to construct a complexity reduced MP-DPD for a 250 Watt Doherty PA, the previously explained procedure lead reduced FIR filters' lengths be equal to *5, 6, 3, 3* and *3*, for filters FIR_1, FIR_3, FIR_5, FIR_7, and FIR_9. Therefore, for every filter, cutting the response length to the last significant tap produced similar results to having an over-fitted problem. Both the full DPD and the complexity-reduced one achieve similar linearization results, demonstrated in figure 3, which shows the output signal of the linearized 250 Watt Doherty PA. One can clearly observe a similar linearization capability (ACPR better than 50 dBc) in both cases, although the number of coefficients was substantially reduced. Hence, with only one set of measurements, the number of coefficients required for implementation was reduced by a factor of 2.5. The simplification is even more significant with regards to model extraction, whose complexity is proportional to the cube of the number of coefficients. In fact, since the PH model is linear in $c_{j,i}$, the coefficients identification algorithm uses the least square error (LSE) optimization method and the calculation complexity of the LSE algorithm is proportional to the cube of the number of unknowns.

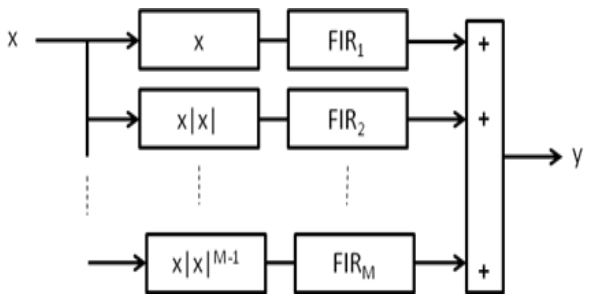

Figure 2 – Parallel Hammerstein Block Diagram

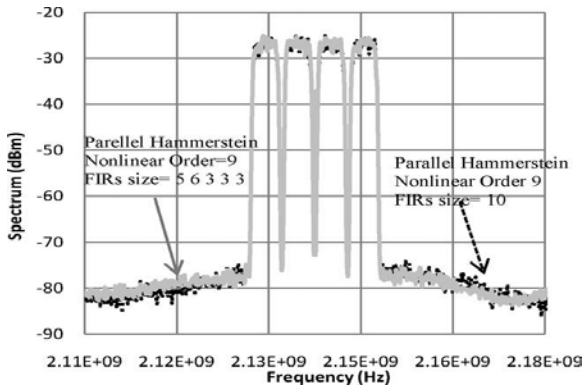

Figure 3 –Output Spectra of PH-DPD linearized PA

2.2. Two Hidden Layers Artificial Neural Network Model Digital Predistorter

The previously mentioned MP-DPD has been successful in linearizing the chosen PA driven with a realistic signal with only 25 coefficients, and an ACPR of better than -50dBc was obtained. MP-DPD, which is certainly a simple topology with a straightforward identification routine, treated the PA as a black box and didn't take into account its physical and circuits' properties. Yet this simplicity, as will be shown in the next section, is achieved at the cost of limited generalization capability which translates to a reduced linearization capability if the characteristics of the signal

used to synthesize the MP-DPD are different from those used when applying it. This weakness may compromise its application for the linearization of PAs in an SDR, since the signal characteristics, such as bandwidth, PAPR, and modulation scheme, change frequently. In this section a recently introduced ANN model is first described. This model, called 2HLANN [2], builds on the ability of ANN to accurately approximate nonlinear functions by judiciously tailoring its structure to the PA circuitry being modeled. The 2HLANN is directly inspired from the PA circuit topology to model its nonlinearity and memory effects rather than curve-fitting the measured data, and consequently has the potential to lessen its sensitivity to the signal characteristics. This reduced sensitivity makes the 2HLANN-DPD more suitable for SDR compared to the MP-DPD, at the expense of additional complexity.

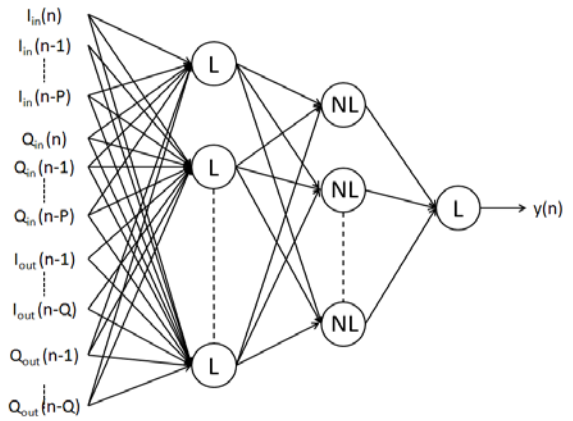

Figure 4 – 2HLANN based model topology.

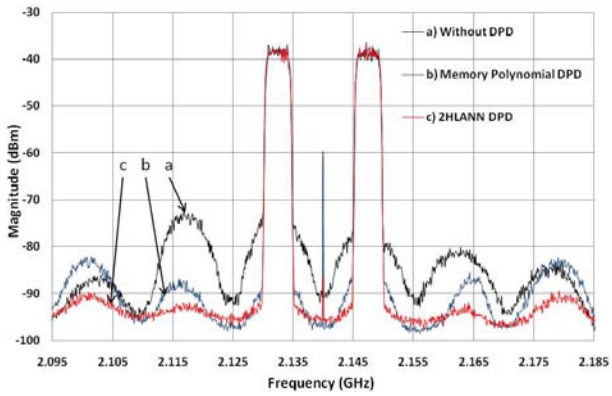

Figure 5 – 2HLANN-DPD Linearized PA output spectra:

Several applications of ANN in the behavioral modeling of nonlinear systems used a single hidden layer as stipulated by the universal approximation theorem. However, the single hidden layer ANN does not always guarantee the widely sought generalization capability. In addition, the universal approximation theorem assumes noise-free training data in order to extract the pattern between the input and the output data. This assumption is generally not met due to the measurement noise encountered when modeling and linearizing PAs. Knowing that the PA behavior is dominated by a static memoryless nonlinearity and a frequency-dependent feedback mechanism behind the memory effects, a two hiden layer ANN structure, shown in the figure 4, is obtained. For that, several nonlinear and linear neurons, denoted as NL and L, respectively, are used to capture the static nonlinearity and the linear components. P and Q designate the input and output memory depths. (I_{in},Q_{in}) and (I_{out},Q_{out}) denote the in-phase and quadrature components of the input and output signals to the PA. Figure 5 depicts the linearized output spectrum of the same 250 Watt Doherty PA, driven with a 1001 WCDMA signal. As per figure 5, the 2HLANN allowed for significant reduction in the out-of-band spectrum emission and an ACPR of higher than 50 dBc at the three frequencies' offsets (10, 15 and 20 MHz). The 2HLANN DPD also outperformed the MP-DPD due to the completeness of the 2HLANN structure.

3. Sensitivity Analysis of Digital Predistortion to the Signal Characteristics

In this section the sensitivity of the previously described DPDs to the variation in signal characteristics will be experimentally analyzed. Indeed, in the previous section the DPD performance was assessed when the signal characteristics (modulation bandwidth, PAPR, PDF, etc.) were kept the same during the DPD construction and execution. The sensitivity analysis is here conducted by measuring the ability of the DPD to maintain good linearization capacity without having to update its parameters despite the variation of the signal characteristics. This study would also examine the robustness of a DPD scheme when deployed in the linearization of multi-mode transmitters. It is worth mentioning that the choice of varying the PDF, the PAPR and the modulation bandwidth is motivated by the independency of the PAs' sources of linear and nonlinear distortions (namely, the transistor, the matching networks, and the biasing networks) on these previously mentioned characteristics [6], and consequently, the corresponding behavioral model is expected to be robust to the changes of those characteristics.

To study the sensitivity of the MP and 2HLANN DPDs to the variation of the signal bandwidth, their construction has been conducted using the largest possible signal bandwidth. Indeed, since the frequency dependency in the matching and the biasing networks is the origin of the memory effect exhibited by the PA, using a signal with the largest bandwidth could be used to construct a generalized DPD having the capacity to capture the distortion (memory effects) of that PA when being applied to linearize a signal with a narrower bandwidth. Accordingly, MP and 2HLANN DPDs were extracted using 4-carriers WCDMA as a characterization signal (20 MHz as a bandwidth), the same DPDs were later used to linearize the 2-carriers WCDMA modulated signal (bandwidth 10 MHz) with a constant PAPR equal

to 7.4 dBm, and an output average power equal to 46 dBm. As shown in figures 6-7 the 2HLANN is less sensitive than the MP to the bandwidth variation. To test the dependency of the considered DPDs on the PAPR variation, the procedure consisted in extracting their coefficients using a 1001 WCDMA signal with a PAPR equal to 9.6 dB. Then, the same DPD will be applied to linearize a 1001 WCDMA modulated signal with a lower PAPR equal to 8 dB (same modulation bandwidth and PDF, Pout=45 dBm). The two DPDs showed similar robustness to the PAPR variation.The frequent change in the network load and its implications on the signal statistics motivated the study of the DPD sensitivity to the signal probability density function. This study was conducted using two signals, a 4 carrier WCDMA and a 1001 WCDMA; the bandwidth of these signals is 20 MHz and the PAPR is 7.4 dBm. These signals have different PDFs. The extraction of the DPD was performed using the 1001 WCDMA signal as a characterization signal and then applied to linearize the 4C WCDMA signal, and compared to the DPD capabilities of the DPD extracted using the 4C WCDMA signal. The two studied DPDs demonstrated comparable robustness to the PDF variation.

Therefore, one can conclude that the 2HLANN DPD is more appropriate in the context of the SDR technology than the MP one, since it preserves the same performance when the signal characteristic changes without having to reconstruct the DPD function. This latter can be explained by the physical inspiration of the 2HLANN DPD that the MP lacks. Indeed, the physical model of the PA made the 2HLANN DPD general enough to incorporate all the sources of nonlinearity and memory effect, and therefore resulted in a general model that captures the behavior of the PA, and not only fit the input and output signals. Besides which, the physically inspired 2HLANN model does not have an infinite degree of freedom that may lead the model in modeling the noise. In fact, the PA block diagram suggested the arrangement of neurons and layers in the 2HLANN model that is essential to capture the optimal model, and therefore to maintain the modeling capabilities when the signal statistics are changed.

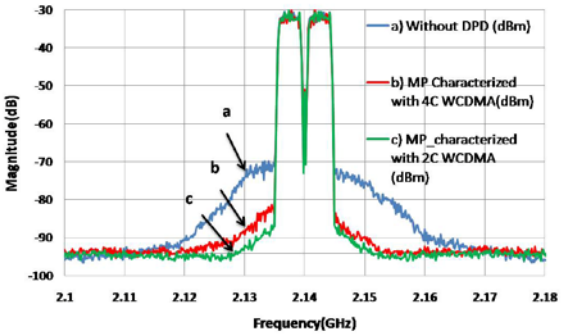

Figure 6. MP-DPD sensitivity to bandwidth variation.

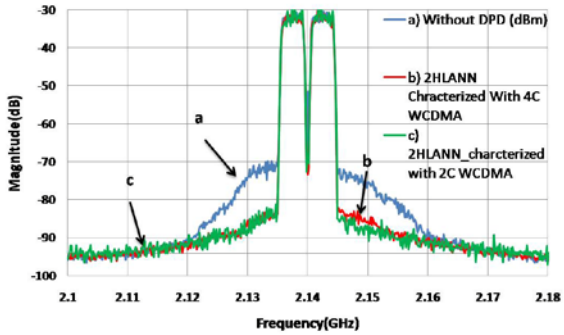

Figure 7. 2HLANN-DPD sensitivity to bandwidth variation

5. Conclusion

This paper examined the sensitivity of the linearization capability of the memory polynomial and the two hidden layer artificial neural networks-based digital predistortion when used in the context of software-defined radio. This latter expects frequent changes of the input signal characteristics depending on the wireless network load. This paper focused on the dependency of the linearization capacity of the MP-DPD and the 2HLANN-DPD on the input signal modulation bandwidth, peak to average power ratio, and probability density function. The experimental study highlighted the importance of the DPD structure and its linkage with the sources of distortions in improving its generality with regards to the input signal characteristics. Indeed, the PA circuitry inspired 2HLANN-DPD showed better robustness to the changes of the input signal characteristics, when compared to the MP-DPD.

6. References

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