A Digital Predistortion Technique Based on a NARX Network to Linearize GaN Class F Power Amplifier

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Abstract - This work presents a novel Digital Predistortion (DPD) scheme based on a NARX network, suitable for linearizing power amplifiers (PAs). The NARX network is a Recurrent Neural Network (RNN) with embedded memory that allows efficient modeling of nonlinear systems. Its neural architecture is very effective to model long term dependencies, such as the typical memory effects of PAs. To demonstrate the feasibility of the NARX network as a DPD system, a GaN class F PA with two LTE signals with 5 MHz of bandwidth is used. Experimental results show a distortion correction better than 10 dB.

INTRODUCTION

Digital Predistortion (DPD) is nowadays the most widely used technique to linearize Power Amplifiers (PAs), due to its high capability to correct distortion using digital signal processing (DSP). Recently, Recurrent Neural Networks (RNN) have provided effective modeling solutions for memory effects of PAs. Different topologies have been proposed to linearize PAs with memory effects. All these include experimental validations with class B, AB or Doherty PAs. There are few published studies that use DPD techniques to linearize class F PA. In this work, we present a novel DPD technique based on an RNN called NARX network. Our proposed DPD model based on NARX network was experimentally validated by using an indirect learning architecture to linearize long term

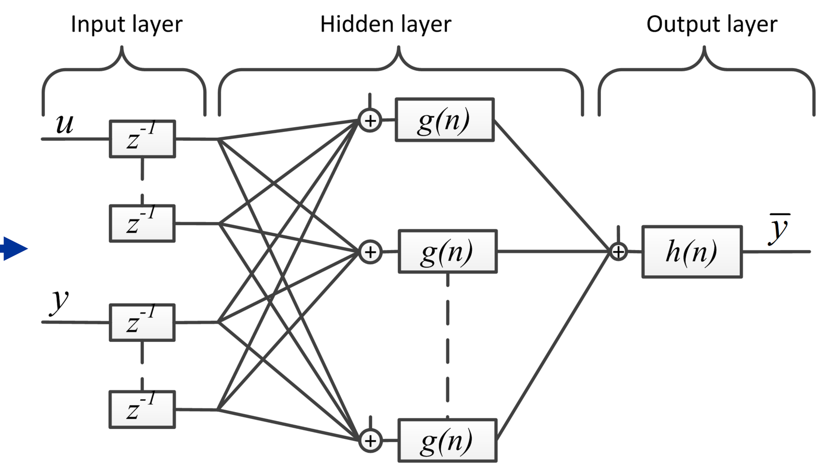
NARX Neural Network

The NARX neural network has a recurrent architecture based on a class of discrete-time nonlinear systems called Nonlinear Autoregressive with eXogenous inputs (NARX), which is mathematically represented by:

$$\tilde{y} = f\left[u(t-1),\dots u(t-du), y(t-1),\dots y(t-dy)\right]$$

When f is approximated by a Multilayer Perceptron (MLP), the topology is called ***NARX neural network.***

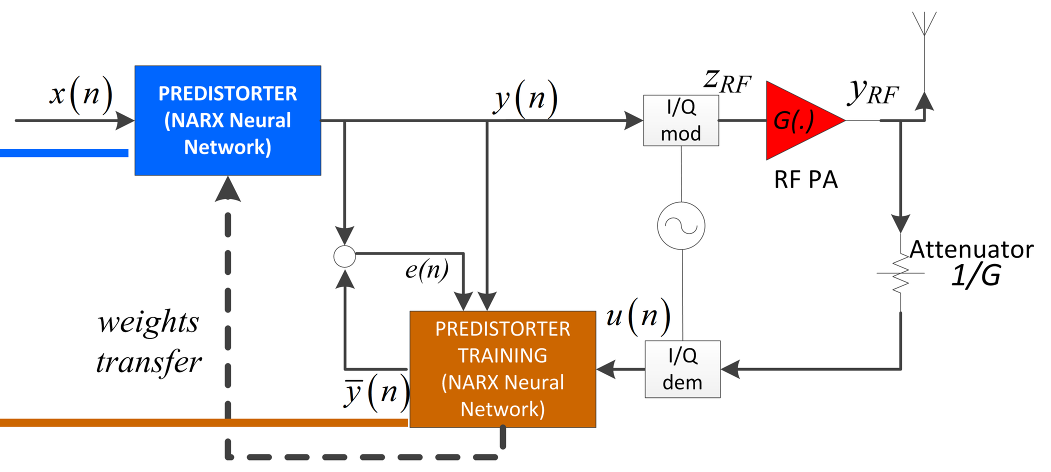
Where, $u(t)$ and $y(t)$: the inputs and outputs of the system at time t, respectively,
du and dy : the embedded input and output memory, respectively,
f is a nonlinear function, that represents the behavior of the system to be modeled.



DPD model with NARX Network

PREDISTORTER block: The neural architecture is used to process the input signal of the PA.

PREDISTORTER TRAINING block: The model of the inverse characteristics of the PA is obtained by the training of the NARX network.



The DPD model with NARX uses an indirect learning architecture and linearize the memory effects of the PA.

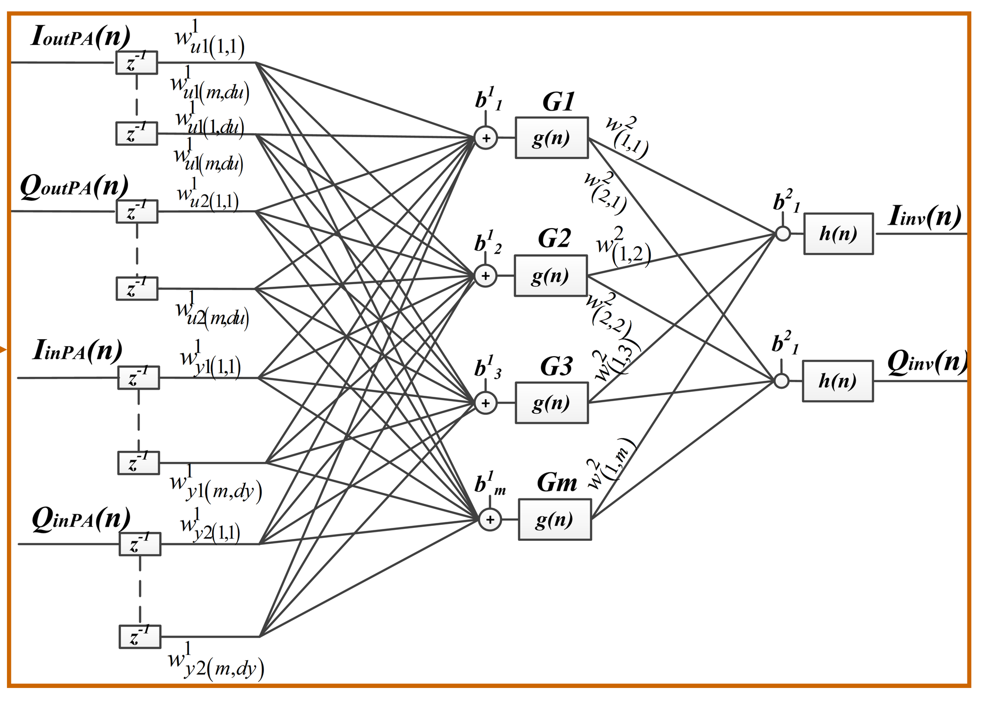


Fig. 3. Neural architecture of the NARX network in the PT block.

The output of the hidden layer *G(k)* for each neuron is given by:

$$G_k(n) = g\left(X_k(n)\right)$$

Where the activation function g is given by a *tansig* function and:

$$X_k(n) = \sum_{j=1}^{du} w^1_{u1(k,j)} I_{outPA}(n-j) + \sum_{j=1}^{du} w^1_{u2(k,j)} Q_{outPA}(n-j) + \sum_{j=1}^{dy} w^1_{y1(k,j)} I_{inPA}(n-j) + \sum_{j=1}^{dy} w^1_{y2(k,j)} I_{inPA}(n-j) + b^1_k$$

being du and dy are the memory order of the input and output, respectively, and $k = 1,2,\dots,m$ are the number of neurons in the hidden layer.

The outputs of the inverse model are :

$$I_{inv}(n) = \sum_{k=1}^{m} w^2_{1k} G_k(n) + b^2_1 \qquad Q_{inv}(n) = \sum_{k=1}^{m} w^2_{2k} G_k(n) + b^2_2$$

Experimental Results

The experimental setup was implemented to linearize a GaN class F PA. The tests are performed under a simulation environment with hardware verification. The GaN class F PA is designed at 2 GHz. The input signal is an LTE with Carrier Aggregation of two contiguous 2x5 MHz components carriers.

The NARX networks parameters to obtain the inverse model of the AM-AM and AM-PM characteristics were: 4 memory order, 10 neurons, 61440 samples divided in training (40%), validation (40%), and test (20%).

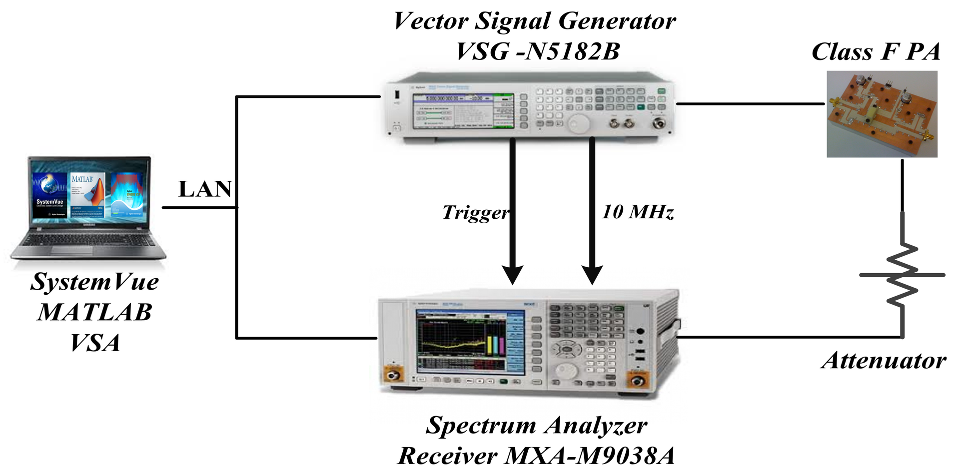


Fig. 3. Measurement setup for the validation of the DPD model based on NARX network.

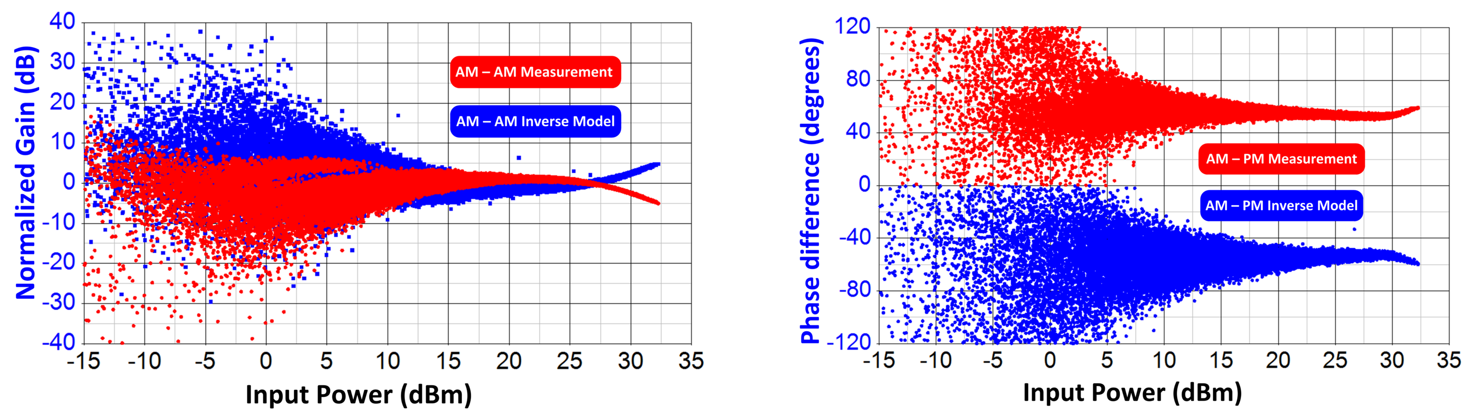


Fig. 4. Comparison of the AM-AM and AM-PM characteristics of the PA between the measurements and the inverse model.

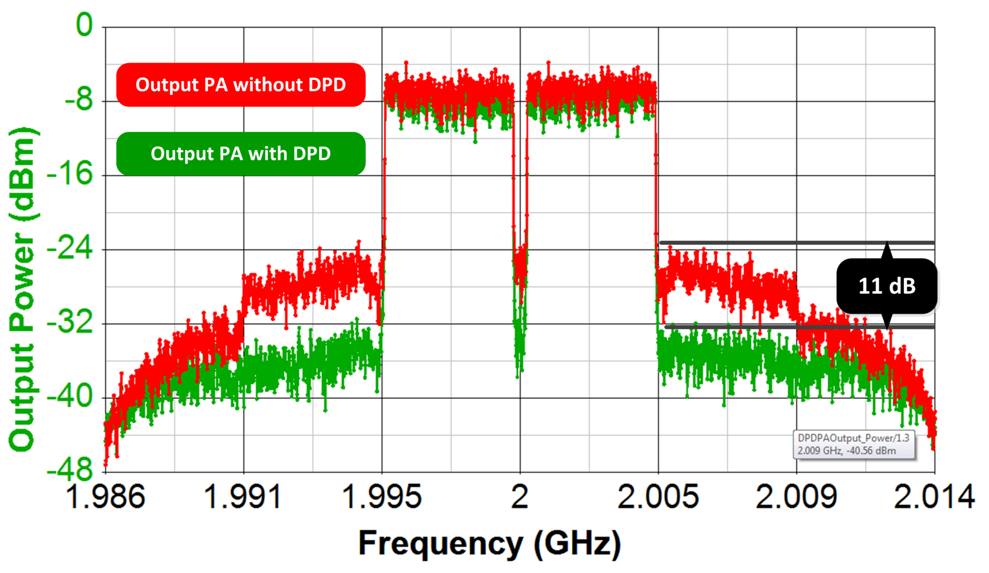


Fig. 5. Performance DPD model based in NARX network .

Conclusions

This paper presents a DPD technique based on a NARX neural network to linearize class F PAs with high nonlinearities and long-term memory effects. The NARX network has a recurrent neural architecture with embedded memory in the input and output that proves to be highly effective to model long-term dependencies, possesses fast convergence and a good generalization performance. The proposed DPD model has the capability of modeling the nonlinearities and the long-term memory effects of the PAs. Experimental results with a class F PA using two contiguous LTE signals centered at 2 GHz, verify the usefulness of the NARX network as an effective DPD scheme for class F PAs.

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