Time-Domain Neural Network Characterization for Dynamic Behavioral Models of Power Amplifiers

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Abstract — **This paper presents a black-box model that can be applied to characterize the nonlinear dynamic behavior of power amplifiers. We show that time-delay feed-forward Neural Networks can be used to make a large-signal input-output time-domain characterization, and to provide an analytical form to predict the amplifier response to multitone excitations. Furthermore, a new technique to immediately extract Volterra series models from the Neural Network parameters has been described. An experiment based on a power amplifier, characterized with a two-tone power swept stimulus to extract the behavioral model, validated with spectra measurements, is demonstrated.**

I. Introduction

The nonlinear analysis of electronic systems often requires an analytical model for each nonlinear element (i.e. an equation representing the input-output relationship), that allows to draw conclusions about the system performance. This approach aims to extract a nonlinear relationship from a relatively simple characterization set, in order to build an input-output model able to generalize the nonlinear dynamic behavior of electronic components for input waveform not used in the characterization set.

Behavioral models try to accurately express the measured behavior of an object, linear or nonlinear, formulating a single closed form equation that represents a measured parameter, which might be a function of multiple independent variables. The process of converting measured data into equations relies on curve-fitting techniques [1]. However, many of the most common techniques are useful where data trace is well behaved over a defined independent variable range and where behavior of an object is known to follow a specific mathematical model, but problems arise when the object's complex internal parameters cause the data trace to exhibit sharp inflections. In that case, data ceases to be well behaved and common curve-fitting techniques become useless. There is a clear need for a new curve fitting technique that provides smoothness and continuity through plotted trace having sharp inflection.

A new technique that could overcome this problem could be the use of Neural Networks. They can help building a behavioral model of a nonlinear element or device. In fact, the Neural Network approach for electronic device modeling has received increasing attention, especially in recent years [2], since model tailoring to the element under study only needs a training procedure based on simulation data or measurements of the physical circuit. Our proposal is not only to use a Neural Network to build a behavioral model for a nonlinear element, but also to obtain an analytical expression for the model, either as neural analytical model and Volterra series expansion, calculated as function of the neural network model parameters (Fig.1).

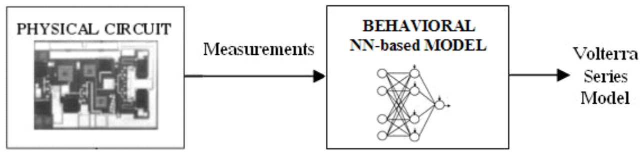

Fig. 1. Novel Behavioral Neural-Network-based approach

As well as the frequency performance of linear devices has been successfully represented by a linear convolution, Volterra series represents its natural extension to nonlinear devices. In such way both a linear and nonlinear dynamic behavior can be usefully represented in a system chain with a black-box model. So far, however, behavioral models based on the Volterra series hold their validity only for weak nonlinearities and require heavy characterization efforts to extract the kernels, especially when multitone intermodulation is a matter of interest.

If the time domain approach is chosen in order to characterize the memory effects adding enough time-delayed inputs to the input-output relation, the question is how to learn the nonlinear behavior response to different input power levels. The answer is that time-delay Neural Networks can learn a nonlinear behavior with medium-to-strong memory effects, along with high-order nonlinearity, if they are trained with input-output time-delayed data samples at different power levels, simultaneously [3]-[4]. This fact turns out of outstanding importance to build behavioral models of power amplifiers which are able to simulate the nonlinear performance with different input spectra and power levels.

A further advantage of this approach is that a new algorithm to extract the Volterra kernels directly from the neural network parameters has been found [5], and the resulting model represents a very good approximation of the nonlinear behavior, with only three-order kernels. This fact can be a useful chance for medium-power analysis, because the neural analytical models can be more complex to implement into simulation CAD tools then compact models based on Volterra series.

In other words, the objective of our work is to develop a new kind of behavioral model for nonlinear RF elements, independent of the physical circuit modeled, which fitting only time-domain device measurements, could train a Neural Network and generate a black-box model on the one hand, and could provide an analytical model for the nonlinear behavior, also in Volterra series form, on the other hand.

In this paper we show, as a case of study, the results obtained from a power amplifier input/output time domain characterization to build both neural and Volterra series based black-box models. The organization of the paper is the following: in the next Section, the Neural Network model proposed is described; in Section III the building of a Volterra model from the neural network parameters is explained; in Section IV the power amplifier characterization and the modeling results are presented. Finally, the conclusions appear in Section V.

II. NEURAL NETWORK MODEL

The neural network frame used in this application is a feed-forward time-delay Neural Network with three layers, an input layer composed of the input time-domain voltage samples and their delayed replies, an hidden layer with nonlinear activation functions, and a linear output layer. The architecture is shown in Fig.2, whereas (1) and (2) are the corresponding input-output analytical expression, for hyperbolic tangent and polynomial activation functions, respectively

$$V_o(t) = d_0 + \sum_{n=1}^{N} c_n \tanh\left[b_n + \sum_{k=0}^{M} w_{nk} V_i(t-kT) \right] \tag{1}$$

$$V_o(t) = d_0 + \sum_{n=1}^{N} c_n \left[b_{nk} + \sum_{k=0}^{M} w_{nk} V_i(t-kT) \right]^P \tag{2}$$

where M is the input memory, N is the number of hidden neurons, and P is the polynomial degree. The particular form of polynomial development in (2) has been chosen because it can be directly implemented in neural network training tools.

The input and output waveform are expressed in terms of their samples in the time domain. The input memory (M) should be chosen in order to adequately represent the memory effects of the behavioral model, in the same manner as done with linear filters, where the number of input taps represents the accuracy in bandwidth shaping. The number of hidden neurons (N) is chosen to perform the best fitting to input-output data without overfitting problems. The Neural Network is trained with a backpropagation algorithm, based on the Levemberg-Marquardt algorithm for network parameters optimization.

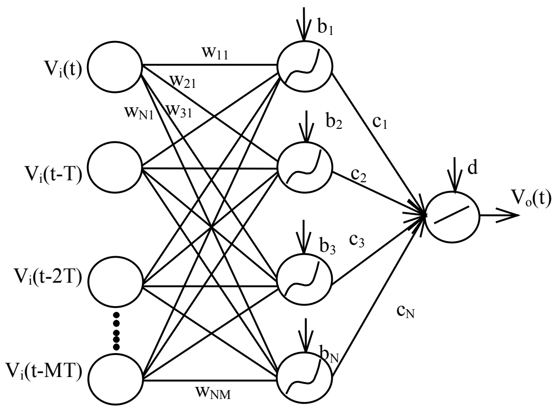

Fig. 2. Time-delay feed-forward Neural Network model

The analytical forms in (1) and (2) can be used as input-output time-domain characterizations for the nonlinear element to model. Furthemore, a Volterra series expansion, calculated in function of the neural network parameters can be extracted from the polynomial output network in (2) as well. This is explained in the next section.

III. VOLTERRA MODEL

A nonlinear dynamic system can be represented exactly by a converging infinite series, that reports the dynamic expansion of a single-input single-output system. This equation is known as the Volterra series expansion, which for third degree expansion can be expressed in the time domain as follows

$$\begin{aligned} V_o(t) &= h_0 + \sum_{k=0}^{M} h_1(k) V_i(t-kT) + \\ &+ \sum_{k_1=0}^{M}\sum_{k_2=0}^{M} h_2(k_1,k_2) V_i(t-k_1T) V_i(t-k_2T) + \\ &+ \sum_{k_1=0}^{M}\sum_{k_2=0}^{M}\sum_{k_3=0}^{M} h_3(k_1,k_2,k_3) V_i(t-k_1T) V_i(t-k_2T) V_i(t-k_3T) \end{aligned} \tag{3}$$

The functions h_0 h_1 h_2 h_3 are known as the Volterra kernels of the system.

The Volterra series analysis is well suited to the simulation of nonlinear microwave devices and circuits, in particular in the weakly and mildly nonlinear regime where a few number of kernels are able to capture the device behavior (e.g. for PA distortion analysis) [6]. The Volterra kernels allow the inference of device characteristics of great concern for the microwave designer. However, the number of terms in the kernels of the series increases exponentially with the order of the kernel and this is the most difficult problem with this approach.

In the Biology field, Wray & Green [8] have outlined a method for extracting the Volterra kernels from the weights and bias values of a Time-delay Multi-Layer Perceptron Neural Network. Based on this idea, there have been several proposals for kernels calculation with different, often non standard, neural networks topologies [8][9]. Our proposed model, instead, it is more general because it could potentially represent not only a dependence on one input variable, but also a function depending on two or more input variables.

Concerning the use of laboratory measurements for feeding a neural model, different models and networks topologies are used and compared, which need complex measurements to train the networks and are based, actually, on numerical estimations. Our proposed approach (applied here to the particular case of power amplifiers), instead, needs only a time domain characterization for the training of the proposed neural network model.

Developing the network output expressed in (2), yields

$$
\begin{aligned}
V_o(t) &= d + \sum_{n=1}^{N} c_n b_n^3 + \sum_{n=1}^{N} c_n \sum_{k=0}^{M} w_{n,k}^3 \left[V_i(t-kT)\right]^3 + \\
&+ \sum_{n=1}^{N} 3c_n b_n^2 \sum_{k=0}^{M} w_{n,k} V_i(t-kT) \qquad (4) \\
&+ \sum_{n=1}^{N} 3c_n b_n \sum_{k_1=0}^{M} \sum_{k_2=0}^{M} w_{n,k_1} w_{n,k_2} V_i(t-k_1T) V_i(t-k_2T) + \\
&+ \sum_{n=1}^{N} 3c_n \sum_{k_1=0}^{M} \sum_{k_2=0}^{M} \sum_{k_3=0}^{M} w_{n,k_1} w_{n,k_2} w_{n,k_3} V_i(t-k_1T) V_i(t-k_2T) V_i(t-k_3T)
\end{aligned}
$$

Comparing terms in (3) and (4), the Volterra kernels of a Volterra series expansion can be easily calculated according to (5)

$$
\begin{aligned}
h_0 &= d + \sum_{n=1}^{N} c_n b_n^3 \\
h_1(k) &= \sum_{n=1}^{N} 3c_n b_n^2 w_{n,k} \\
h_2(k_1,k_2) &= \begin{cases} \sum_{n=1}^{N} 6c_n b_n w_{n,k_1} w_{n,k_2} \\ \sum_{n=1}^{N} 3c_n b_n w_{n,k_1} w_{n,k_2} & (k_1 = k_2) \end{cases} \qquad (5) \\
h_3(k_1,k_2,k_3) &= \begin{cases} \sum_{n=1}^{N} 3c_n w_{n,k_1} w_{n,k_2} w_{n,k_3} \\ \sum_{n=1}^{N} c_n w_{n,k}^3 & (k_1 = k_2 = k_3 = k) \end{cases}
\end{aligned}
$$

The Volterra model extracted in this way is perfectly equivalent and performs the same degree of accuracy as the Neural Network itself. This is of great importance because is very easy and fast to train a polynomial Neural Network and to extract the correspondent Volterra model.

IV. Model Training and validation

For training purpose, a Cernex 2266 power amplifier, with a 1-2 GHz bandwidth, a 29 dB gain, and 1 dB compression at 30 dBm, has been stimulated with two tones with central frequency at 2 GHz and frequency spacing 100 MHz, from two synthesized sweepers, each one ranging the power from –20 to +1 dB, that is 2 dB over the 1 dB compression point of the amplifier. The amplifier output has been connected to a Tek11801B Digital Sampling Oscilloscope, and 5120 samples has been collected on a 20 ns window. The oscilloscope has been triggered with the common RF reference at 10 MHz from the generators; two commensurate frequencies multiple of the trigger frequency have been used for this purpose. The data samples have been read with a Labview program from a PC, connected to the oscilloscope via an GPIB interface. The characterization setup is shown in Fig.3.

Input data vectors from different input levels have been first joined together, to train the Neural Network with all power levels, simultaneously; the resulting vector has been copied and delayed as many times, to represent the network input, as necessary to take into account memory effects. The tap delay must be a multiple or equal to the data sampling time T_S, and is calculated from $T = nT_S = n\left(F_S\right)^{-1} = \left(2*BW\right)^{-1}$ to avoid spectral aliasing, where F_S is the data sampling frequency and BW the desired characterization bandwidth.

Two type of networks have been trained: the former, with sigmoidal activation function, in the entire power range, with 3 dB power step, to perform a very large signal nonlinear model, the second, with third degree polynomial activation function, in a smaller power range, below 1 dB compression point. Both have been trained with 8 input delays and 9 hidden neurons. Training results are shown in Figg.4 and 5.

On the other hand, for validation purpose, frequency domain amplifier response, obtained from FFT transform of time-domain simulation waveform of the two behavioral models and the amplifier time-domain measurements, has been compared, to demonstrate the validity of the modeling approach also in the frequency domain. Results are shown in Figg. 6 and 7. As it can be seen spectra are very close in the amplifier bandwidth, both for low and high distortion. The third order Volterra model is well behaved near 1 dB compression (Pin = -5 dB), whereas the sigmoidal model hold its validity up to Pin = +1 dB, 2 dB over the 1 dB compression.

V. Conclusions

A new large-signal behavioral model, based on Time-Delay Neural Networks, for the nonlinear dynamic modeling of power amplifiers, has been developed. Moreover, an easy procedure to extract Volterra kernels from the polynomial network parameters provide a very compact and accurate model to be used below 1dB compression point. Future developments, which rely on a more accurate time-domain characterization with a Large Signal VNA, could enhance the accuracy of the modeling approach.

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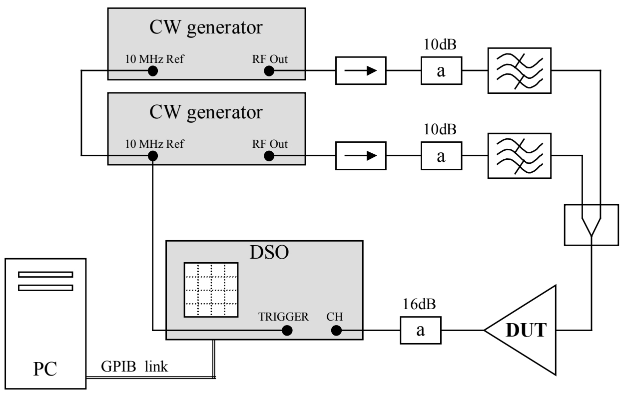

Fig.3. Measurement setup for PA time-domain characterization.

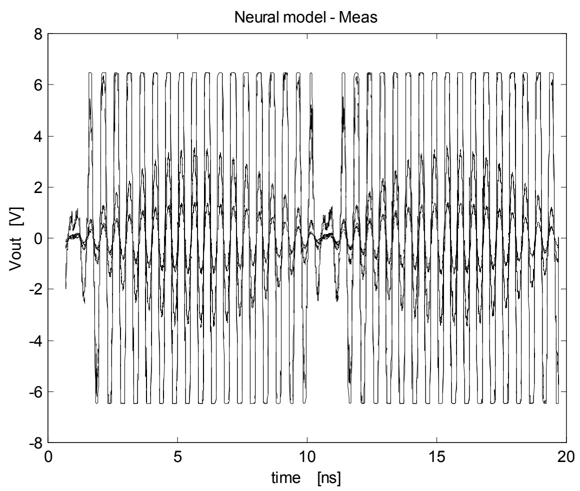

Fig.4. Sigmoidal neural model simulation and amplifier measurement comparison for three input power levels (-20, -12, +1 dBm).

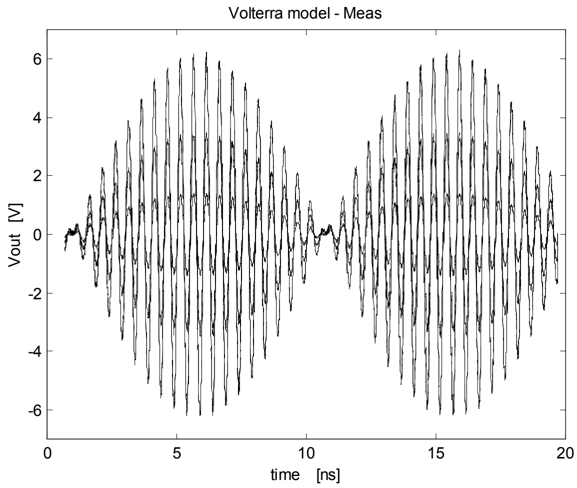

Fig.5. Volterra model simulation and amplifier measurement comparison for three input power levels (-20, -12, -7 dBm).

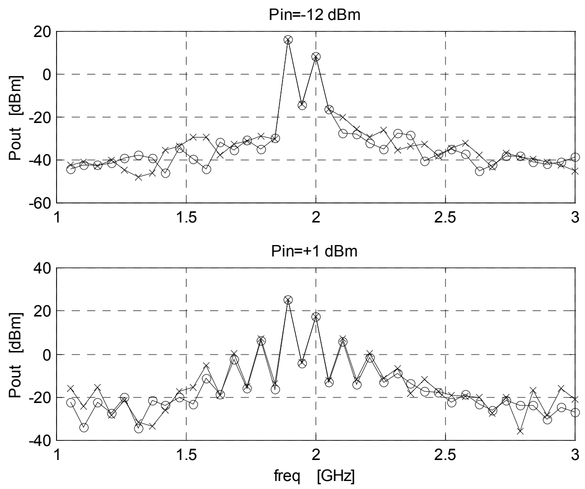

Fig.6. Sigmoidal neural model (o) and amplifier (x) output spectra comparison for two input power levels (-12, +1 dBm).

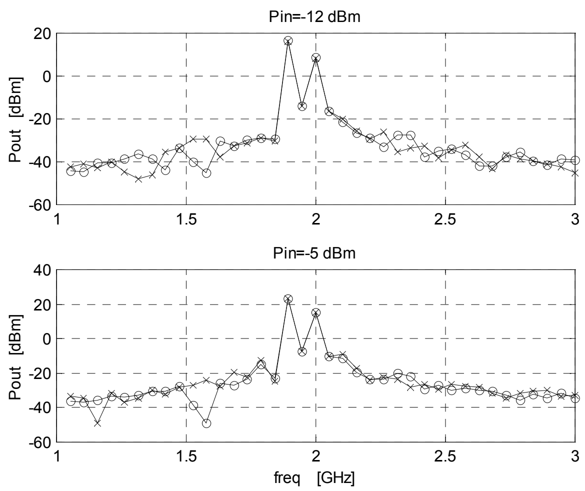

Fig.7. Volterra model (o) and amplifier (x) output spectra comparison for two input power levels (-12, -5 dBm).