Neural-Based Nonlinear Device Models for Intermodulation Analysis

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***Abstract* — A new procedure to learn a nonlinear model together with its derivative parameters using a composite neural network is presented. So far neural networks have never been used to extract large-signal device model accounting for distortion parameters. Applying this method to FET devices leads to nonlinear models for current-voltage functions which allow improved prediction of weak and mildly device nonlinearities in the whole bias region. The resulting models have demonstrated to be suitable for both small-signal and large-signal analyses, including intermodulation distortion prediction.**

I. Introduction

Device models based on nonlinear equivalent circuit for the available commercial CAD/CAE programs that use Harmonic Balance techniques, require associated current-voltage and charge-voltage mathematical model, described from a closed-form function of the intrinsic control voltages, to characterize the nonlinear circuit elements.

It is generally acknowledged that any nonlinear model should match simultaneously the general form and the first and higher order derivatives of the nonlinear function that represents the modeled nonlinearity [1,2]. Many FET's models have been proposed in which derivatives are properties of concern for accurate calculation of intermodulation distortion. Weak and mildly device nonlinearities can be modeled through distortion parameters extracted from small-signal harmonic measurements.

So far neural networks have been used to learn derivative parameters only in small-signal Volterra series analysis [3,4,5]. In the Volterra approach a third degree truncated bidimensional power series must be supplied, where $v_g = V_g - V_{g0}$ $v_d = V_d - V_{d0}$ are the incremental intrinsic gate and drain voltages respect to the bias voltgages, and I_{dc} the dc drain-source current:

$$\begin{aligned} I_{ds}(V_g, V_d) = {} & I_{dc}(V_{g0}, V_{d0}) + \\ & + G_m v_g + G_d v_d + \\ & + G_{m2} v_g^2 + G_{d2} v_d^2 + G_{md} v_g v_d + \\ & + G_{m3} v_g^3 + G_{d3} v_d^3 + G_{m2d} v_g^2 v_d + G_{md2} v_g v_d^2 \end{aligned} \tag{1}$$

The series coefficents are the corresponding derivatives of current calculated at the quiescent point,

$$G_{m_p d_q} = (p!)^{-1} (q!)^{-1} \frac{\partial^p I_{ds}}{\partial^p V_g} \frac{\partial^q I_{ds}}{\partial^q V_d} \tag{2}$$

It was already demonstrated that neural networks can represent a powerful tool to match, simultaneously, the model input/output data and its derivative information in the entire operational bias region [6]. In this way distortion parameters can be learned by neural networks not only for small-signal analysis, but also for large-signal analysis in mixer and power amplifier design.

Neural networks are used to match, simultaneously, in each bias point, the nonlinear I-V characteristic, based on static or pulsed measurements, the first-order derivative parameters corresponding to the linear equivalent circuit elements (G_m,G_d) extracted from linear power measurement or S-parameter measurements [6,7], and higher-order parameters (G_{m2},G_{d2},G_{md} ecc.) extracted from small-signal harmonic or intermodulation measurements at the bias point. Actually, these measurements are performed only in those bias regions of major concern for weak nonlinearities, where they are the only causes of device nonlinearity, that is resistive region for mixer design, or saturation region for power amplifier design. The proposed approach has been applied to the extraction of the large-signal model of power HEMT devices. An experiment based on a 0.25x1000µm medium power GaAs HEMT is discussed.

II. Model Extraction

Starting from the nonlinear equivalent circuit of an HEMT device shown in Fig.1, all nonlinear elements have been extracted fitting the neural sigmoid functions to experimental measurements. In order to fit, simultaneously, the nonlinear model and its derivative parameters, a composite neural network has been built, with sub-networks corresponding to the model to learn and to its derivative parameters, respectively [7]. The network topology is presented in Fig.2, showing data boxes corresponding to the measured first and higher order distortion parameters. The sub-networks are obtained from corresponding mathematical derivatives of the main network output. Weights in derivative sub-networks are bonded to those in main network. In ref. [6] a practical approach to modify the network Jacobian of a standard neural network tool is explained. However, when the derivative order of parameters to match increases, a user-defined neural network is more simple to handle [8].

Although the gate-source capacitance C_{gs}, I_{ds} is by far the element of the FET's equivalent circuit model that mostly contribute to the nonlinear behavior of the device. For this reason nonolinear charge models have been obtained integrating only the linear equivalent circuit charges, using the composite network up to the first-order.

In order to extract the I_{ds} current higher order derivative parameters, starting from (1), the approach based on the nonlinear currents method presented by Maas in [1] has been followed. The 2nd and 3rd order I_{ds} dependence from V_d has been neglected in this case, and only parameters G_{m2} and G_{m3} have been calculated from 2nd and 3rd harmonic power ratios [2]. To measure the distortion ratios on a HP71000 spectrum analyzer, the gate is driven by a low level VHF signal at 400 MHz. At low frequencies there is almost no FET's internal feedback, and reactive elements effect have been neglected. Results for Gm2 and Gm3 are plotted in Fig.3 and Fig.4. However, the other parameters can be also extracted with the same approach, performing measurements with more than one output termination.

III. Model Validation

After inserted into a commercial CAD simulator, the small- and large-signal behavior of the model has been simulated. Results for S-parameters model performance are shown in Fig.5. Comparison with one-tone harmonic to carrier measurements at 5 GHz, 50 Ω termination, are reported in Fig.6. The neural model simulation is close to the device nonlinear behavior.

Conclusions

This approach has demonstrated to be a simple tool to perform accurate large-signal models, which are well-suited to predict nonlinear device behavior up to third-order distortion. These models have been already used for mixer and power amplifier design.

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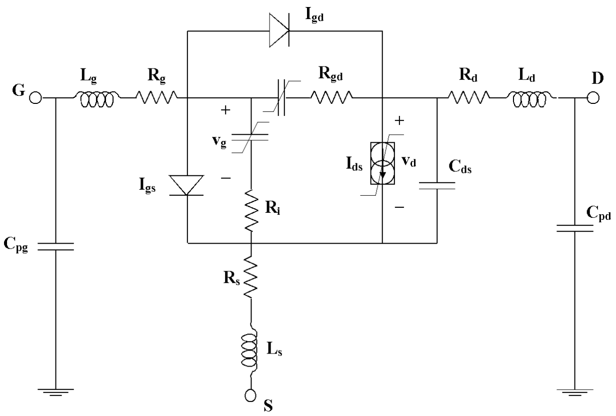

Fig.1. HEMT nonlinear equivalent circuit

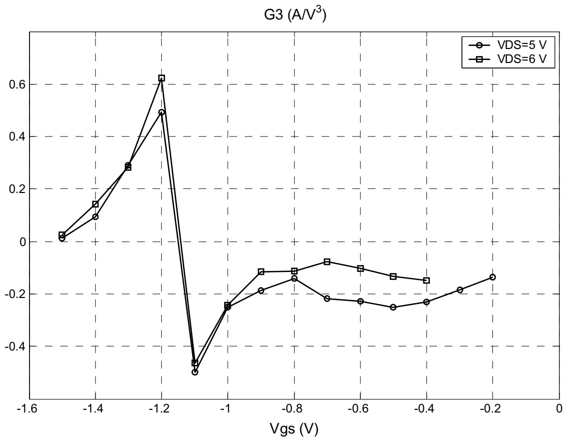

Fig.4. Gm3 parameter extracted from 3rd harmonic measurements.

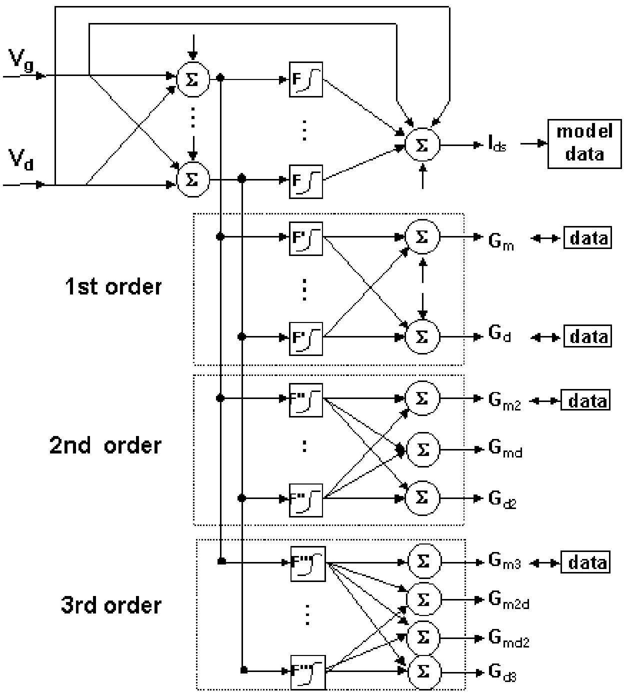

Fig.2. Composite neural network architecture for extraction of Ids nonlinear mathematical model from 1st order, 2nd order and 3rd order derivative parameters.

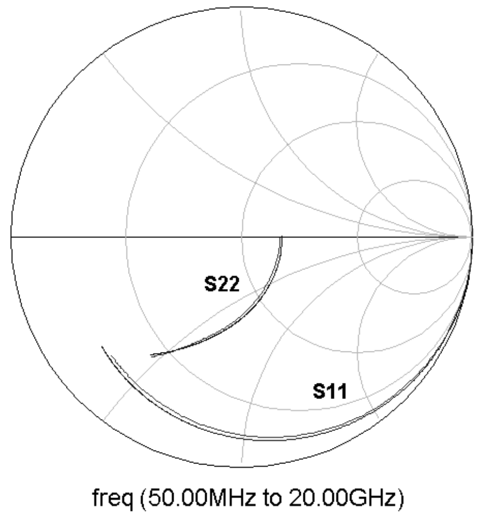

Fig.5. S-parameters comparison between measurements and neural model simulation.

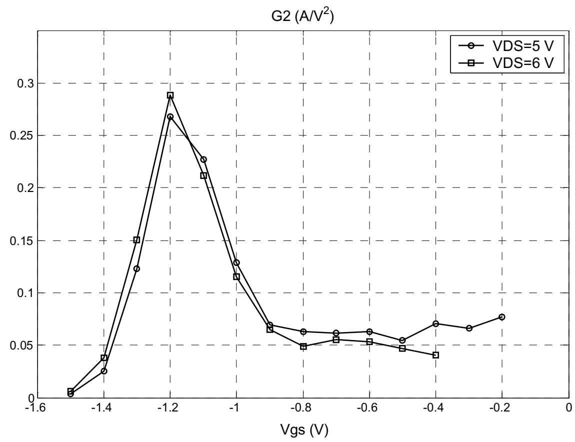

Fig.3. Gm2 parameter extracted from 2nd harmonic measurements.

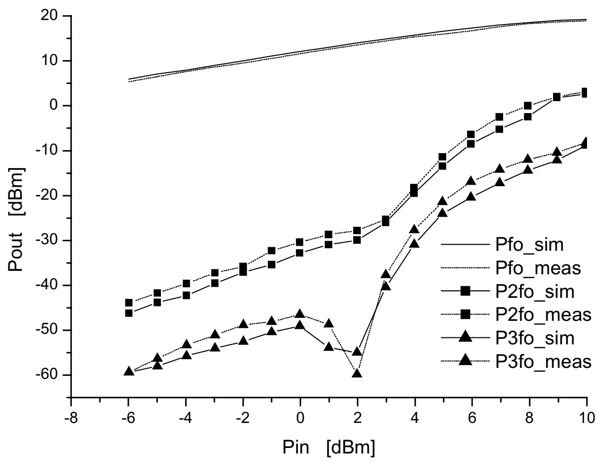

Fig.6. Comparison between model simulation and mesurements of output fundamental, 2nd and 3rd harmonic powers.