# Distortion Characterization and Neural Network Modeling for Microwave Devices

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***Abstract* — A new method for characterization of HEMT distortion parameters, which extracts the coefficents of Taylor series expansion of $I_{ds}(V_{gs},V_{ds})$, including all cross-terms, from low-frequency harmonic measurements, has been developed. The extracted parameters will be used either in a Volterra series model around a fixed bias point for third order characterization of small-signal $I_{ds}$ nonlinearity, and in a large-signal model of $I_{ds}$ characteristic, where its partial derivatives have been locally characterized up to the third order in the whole bias region, using a novel neural network representation. The two models have been verified by harmonic measurements on a AMS HEMT at 5 GHz.**

## I. Introduction

It is generally acknowledged that any nonlinear model should match simultaneously the I/V or Q/V characteristic and its first three derivatives to achieve accurately third order distortion prediction of weakly and mildly nonlinear electronic device [1][2]. In fact, it is possible to show that the levels of third order intermodulation components depend most strongly on the third and lower derivatives of the dominant I/V or Q/V nonlinearities. For sake of clarity, since the drain current $I_{ds}$ is by far the element of the FET model that mostly contributes to the device nonlinear behaviour, this work has been focused on this nonlinearity modeling. In the complete device model, however, also gate charges have been nonlinearly modeled, but their characterization is limited to first order derivatives.

Several techniques to characterize the distortion parameters of nonlinear devices are already available. When distortion parameters are obtained via the calculation of the derivatives of static $I_{ds}(V_{gs},V_{ds})$ measured data, errors due to the measurement noise and low frequency dispersion are just exacerbated by derivatives, and hide the nonlinear properties. On the other hand, when pulsed measurements are employed to model $I_{ds}$ behavior, only first order nonlinearities are characterized as well, but measurement errors could perfectly hide higher order dependence in a mildly nonlinear device. In this paper we demonstrate that device nonlinearities can be accurately modeled through $I_{ds}$ distortion parameters extracted from small-signal harmonic measurements. Among the most interesting methods based on intermodulation measurements, in [3] two-sided noncommensurate excitations and the extraction of Volterra kernels are required, whereas in [4] extrinsic elements of the equivalent circuit are incorporated in the nonlinear model, and equations are approximated, decreasing the accuracy of the model in distortion prediction near 1 dB compression point.

In this paper we propose a new extraction technique applying the nonlinear current method of Volterra series [1][2] to the nonlinear equivalent circuit, in which system equations are obtained changing as many drain loads as the number of distortion parameters of the same order to extract from one-tone harmonic measurements. Starting from calculations on a memoryless equivalent circuit with resistive loads at low frequency, the method has been generalized including the effect of parasitics and using an output tuner loadpull, for RF characterization at microwave frequencies.

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 characterizes the small-signal nonlinear distortion in the whole bias region.

Even if we are aware that intermodulation distortion (IMD) is also an important parameter for most microwave applications, only one-tone analysis will be considered in this work. However, IMD is directly related to harmonic distortion (HD) by simple relations in the case of weak nonlinearities.

In recent years, the Harmonic Balance technique and Volterra-series expansion have been widely used in the microwave nonlinear simulations with noncommensurate excitations. From device modeling point of view, all that is necessary for Volterra-series analysis in a small-signal regime is a Taylor-series expansion of the device nonlinearities around a fixed bias point for amplifier simulation or around a time-varying large-signal waveform for mixers. On the other hand, to perform large-signal analysis, 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. In this paper both modeling approach have been followed and validated by power measurements.

It was already demonstrated that neural networks can provide a large-signal description from the small signal linear elements dependence with the bias voltages [5] or from pulsed measurements [6]. In this work neural networks are used to match, simultaneously, in each bias point, the nonlinear I/V characteristic, based on DC or pulsed measurements, and its derivative parameters up to the third order [7].

An experiment based on a 0.25x10x100 μm medium power GaAs HEMT from Alenia-Marconi System (AMS) foundry is discussed.

## II. Distortion Characterization

The extraction of $I_{ds}$ derivative parameters from power measurements can be accomplished more quickly applying the nonlinear current method to the equivalent circuit of Fig.1, where the transisor is almost unilateral, because of the low frequency used. It is an iterative technique that allows the calculation of the nonlinear $I_{ds}$ component of order (n+1), given the control voltages of order (n), and assuming that the first order response is obtained by linear solution.

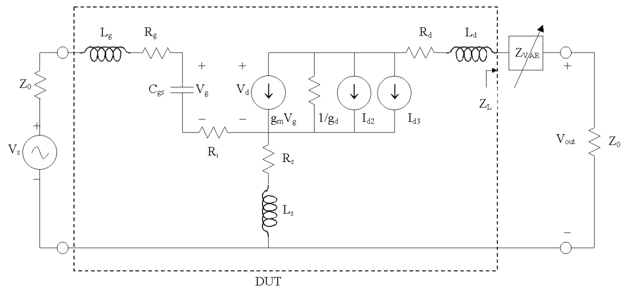


Fig.1. Equivalent circuit for distortion parameters extraction.

Considering incremental voltages and currents in the time domain (small letters):

$$i_d(t) = i_{dlin} + i_{d2} + i_{d3} \tag{1}$$

$$\begin{aligned} i_d(t) &= g_m v_g + g_d v_d + \\ &+ g_{m2} v_g^2 + g_{d2} v_d^2 + g_{md} v_g v_d + \\ &+ g_{m3} v_g^3 + g_{d3} v_d^3 + g_{m2d} v_g^2 v_d + g_{md2} v_g v_d^2 \end{aligned} \tag{2}$$

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

$$g_{m_p d_q} = (p!)^{-1} (q!)^{-1} \frac{\partial^p i_d}{\partial^p v_g} \frac{\partial^q i_d}{\partial^q v_d} \tag{3}$$

Separating voltage and current orders, yields

$$\begin{aligned} v_d &= v_{d1} + v_{d2} + v_{d3} \\ v_d^2 &= v_{d1}^2 + 2 v_{d1} v_{d2} \qquad v_d^3 = v_{d1}^3 \end{aligned} \tag{4}$$

$$\begin{aligned} v_g &= v_{g1} + v_{g2} + v_{g3} \\ v_g^2 &= v_{g1}^2 + 2 v_{g1} v_{g2} \qquad v_g^3 = v_{g1}^3 \end{aligned} \tag{5}$$

$$\begin{aligned} i_{dlin} &= g_m v_g + g_d v_d \\ i_{d2} &= g_{m2} v_{g1}^2 + g_{md} v_{g1} v_{d1} + g_{d2} v_{d1}^2 \\ i_{d3} &= 2 g_{m2} v_{g1} v_{g2} + g_{md} (v_{g2} v_{d1} + v_{g1} v_{d2}) + \\ &+ 2 g_{d2} v_{d1} v_{d2} + \\ &+ g_{m3} v_{g1}^3 + g_{m2d} v_{g1}^2 v_{d1} + g_{md2} v_{g1} v_{d1}^2 + g_{d3} v_{d1}^3 \end{aligned} \tag{6}$$

In the frequency domain (capital letters):

$$Z_{gs} = R_0 + R_g + j\omega L_g + R_i + \frac{1}{j\omega C_{gs}} \qquad R_0 = 50\,\Omega$$

$$Z_s = (R_s + j\omega L_s) // Z_{gs} \qquad Z_{net} = R_d + j\omega L_d + Z_L + Z_s$$

For 1st order:

$$V_{d1} = \alpha(\omega_1) V_s \qquad V_{g1} = \beta(\omega_1) V_S + \gamma(\omega_1) V_{d1} \tag{9}$$

For n-order: $V_{dn} = -(g_m V_{gn} + g_d V_{dn} + I_{dn}) Z_{net}$

$$V_{dn}(\omega) = -\frac{1}{\lambda(\omega)} I_{dn}(\omega) \qquad V_{gn} = \delta(\omega) V_{dn} \tag{10}$$

The method allows to find voltages and currents order by order following the hierarchy:

$$V_{d1} \to V_{g1} \to I_{d2} \to V_{d2} \to V_{g2} \to I_{d3} \to V_{d3}$$

Switching from frequency to time domain, it is easy to obtain the $V_d$ harmonic phasors:

$$\begin{aligned} v_d(t) &= v_{d1}(t) + v_{d2}(t) + v_{d3}(t) = \\ &= \frac{1}{2}[V_{d1}(\omega_1) + V_{d3}(\omega_1)] e^{j\omega_1 t} + \\ &+ \frac{1}{2} V_{d2}(2\omega_1) e^{j2\omega_1 t} + \frac{1}{2} V_{d3}(3\omega_1) e^{j3\omega_1 t} \end{aligned} \tag{11}$$

Noting that: $V_{out}(\omega) = V_d(\omega) \dfrac{R_0}{Z_{net}(\omega)}$

$$P_{out} = \frac{1}{2} \frac{|V_{out}|^2}{R_0} = \frac{1}{2} \frac{R_0}{|Z_{net}|^2} |V_d|^2$$

it is possible to extract $V_d$ phasors from harmonic measurements, that is the power gain

$$G_P = \frac{P_{out1}}{P_{in}} = \frac{R_0}{2 P_{in} |Z_{net}(\omega_1)|^2} |V_{d1}(\omega_1) + V_{d3}(\omega_1)|^2 \tag{11}$$

and the harmonic distortion ratios

$$HDR2 = \frac{P_{out2}}{P_{out1}} = \frac{1}{2 P_{in} G_p} \frac{R_0}{|Z_{net}(2\omega_1)|^2} |V_{d2}(2\omega_1)|^2 \tag{12}$$

$$HDR3 = \frac{P_{out3}}{P_{out1}} = \frac{1}{2 P_{in} G_p} \frac{R_0}{|Z_{net}(3\omega_1)|^2} |V_{d3}(3\omega_1)|^2 \tag{13}$$

To measure the distortion ratios on a HP71000 spectrum analyzer, the gate must driven by a one-tone excitation with input frequency less than 100-200 MHz for an input power level of -20 dBm well below the 1dB compression point where Volterra calculations are valid. The measurement setup is shown in Fig.2. At these frequencies there is almost no FET's internal feedback. First, the three $V_d$ order components can be obtained analitically, if the third order contribution to first order can be neglected, that is input power is low enough. Alternatively $V_d$ components can be extracted via an optimization algorithm. Then, each order $V_d$ component creates a system of two, three and four quadratic equations, in the unknown distortion parameters (Gm, Gd), (Gm2, Gmd, Gd2) and (Gm3, Gm2d, Gmd2, Gd3), respectively, that can be solved via an optimization algorithm based on least-square fitting. From above equations it can be seen that the n-order $V_d$ component depends on derivative parameters of order ≤ n. It follows that systems solution goes on from low to high order.

A complexity reduction in the characterization method can be obtained if the tuned load is real, and $C_{gs}$ effect is neglected. In this case the three systems become linear, and parameters can be yield from matrix inversion. Both methods generate well conditioned systems.

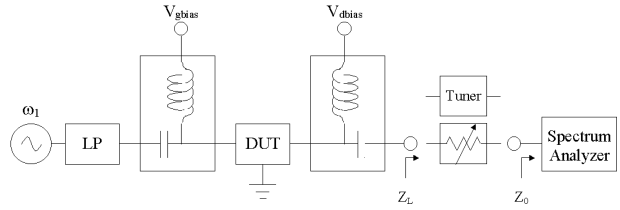


Fig.2. Harmonic measurement setup.

The measure of IM ratios, however, gives no information about phase. With complex loads, the optimization algorithm looks for the right system solution, imposing the constraint of real derivatives. In the case of real loads, equations give two possible values of $V_d$ components, but only one can be correct, and it is easy to select the correct one. For example, if Gm2 decreases as $V_{gs}$ increases, Gm3 should be negative.

The obtained results for $I_{ds}$ parameters are plotted in Fig.3, for the characterization method employing four resistive series loads (47,75,100,150 Ω), a fundamental frequency of 15 MHz to neglect the reactive behavior of the resistive loads, and an input power ranging around -20 dBm, with slight differences between each bias point.

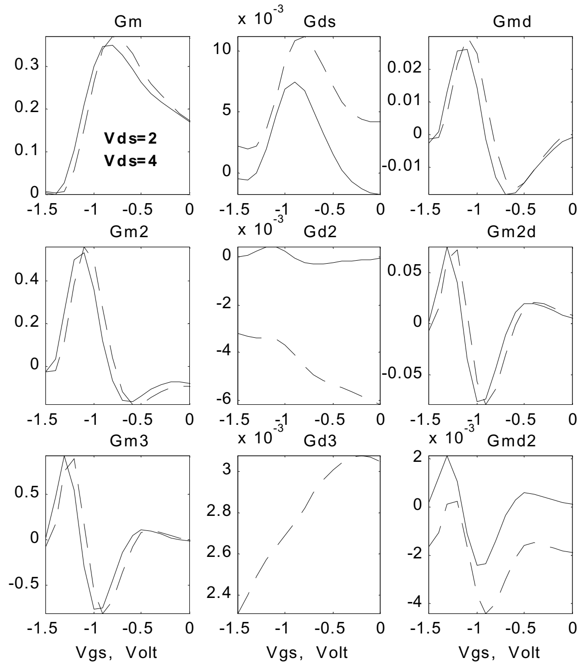


Fig.3. Ids derivative parameters extracted from harmonic measurements for Vgs=(-1.5...0.0) V and Vds=4 V (continuous) and Vds=2 V (dashed).

## III. Neural Network Modeling

The extracted derivative parameters can be used to build a small-signal bias-dependent power-series $I_{ds}$ model such as in (2), for low power level nonlinear analysis. On the other hand, the extracted parameters can be used to condition an $I_{ds}$ large-signal model derivatives at each bias point. Neural networks have been already used to fit any nonlinear model and its derivatives using sigmoidal activation function [7]. The analytical model for $I_{ds}$ current resulting from a sigmoidal neural network with just one hidden layer is

$$I_{ds}(V_{gs},V_{ds}) = e + d_1 V_{gs} + d_2 V_{ds} + \sum_{i=1}^{N} c_i \tanh\left(b_i + a_{i1}V_{gs} + a_{i2}V_{ds}\right) \qquad (14)$$

derivatives of which can be analytically obtained and associated to correspondent neural networks. In order to fit, simultaneously, the nonlinear model and its derivatives, a global derivative neural network (GDNN) can be defined, with sub-networks corresponding to the model to learn and to its derivatives, respectively [7]. The network topology is presented in Fig.4, showing data sources for each output parameter to fit. The first-order model derivatives correspond to the linear equivalent circuit elements ($G_m$,$G_d$) extracted from first-order harmonic measurements or S-parameter measurements, whereas second and third order derivatives to parameters ($G_{m2}$,$G_{d2}$,$G_{md}$ ecc.) extracted from harmonic measurements.

It is worth noting that weights and bias in derivative sub-networks are dependent from those in the main network, which are the only optimizable parameters. In [7] a practical approach to modify the network Jacobian in a Levemberg and Marquardt optimization of a standard neural network tool is explained. However, when the derivative order of parameters to match increases that method becomes unwieldy, and a user-defined learning algorithm is better to handle.

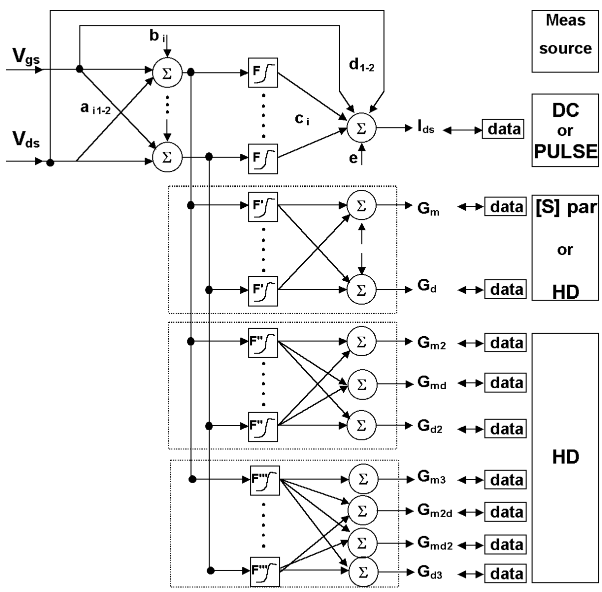


Fig.4. Global neural network architecture.

Starting from the nonlinear equivalent circuit of an HEMT device shown in Fig.5, all nonlinear elements have been extracted fitting the neural sigmoid functions to experimental measurements.

Large-signal behaviour has been characterized only through the fast curvature of I/V characteristic evaluated through DC measurements, such as current cutoff below pinch-off voltage, forward current at the Gate Schottky, linear to saturated regions transition and avalanche breakdown from drain to gate.

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 nonlinear charge models have been obtained fitting only the first order derivatives (i.e. the capacitances) to circuit parameters extracted from linear measurements.

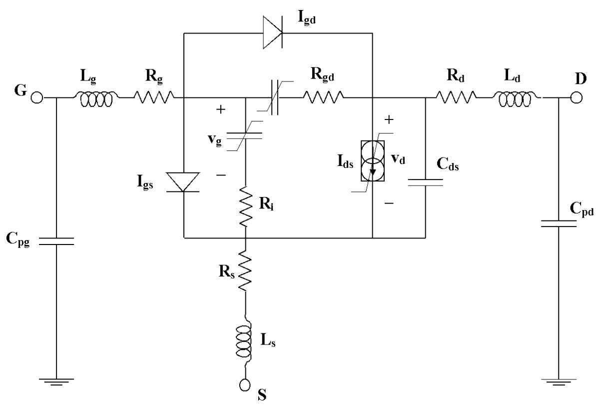


Fig.5. HEMT nonlinear equivalent circuit.

## IV. Model Validation

Two device models based on the nonlinear circuit of Fig.5 have been built. The first model employes the Volterra series expansion for $I_{ds}$ current described in (2) around the bias point $V_{gs}$=-0.5 V and $V_{ds}$=4V, using the corresponding extracted parameters, the second one is the large-signal model resulted from the GDNN training.

After inserted into a commercial CAD simulator, both models have been simulated in Harmonic Balance analysis. Comparison with one-tone harmonic to carrier measurements at 5 GHz, 50 Ω termination, performed on-wafer on a 0.25x10x100 µm medium power GaAs HEMT from Alenia-Marconi System (AMS) foundry, are reported in Figg. 6 and 7 for the fundamental and harmonic output powers, respectively. As expected, Volterra-series model provides the nonlinear behavior prediction well before the 1-dB compression point, whereas the large-signal neural model is very close to measurements also for high distortion levels.

## V. Conclusions

This approach has demonstrated to be a useful tool to perform accurate small-signal and large-signal models, which are well-suited to predict nonlinear device behavior up to third-order distortion. Despite of its intrinsic small-signal characterization, the large-signal model has demonstrated to be able to predict the nonlinear behavior also for high distortion levels, thanks to its local derivative characterization up to the third order.

## References

[1] S.A.Maas, Nonlinear Microwave Circuits, Norwood, MA, Arthec House, 1988.

[2] J.C.Pedro, N.B.Carvalho, Intermodulation Distortion in Microwave and Wireless Circuits, Artech House, 2003.

[3] J.C.Pedro and J.Perez, Accurate Simulation of GaAs MESFET Intermodulation Distorsion Using a New Drain-Source Current Model, IEEE Trans. Microwave Theory and Techniques, 42 (1), January 1994, 25-33.

[4] G.Qu, A.E.Parker, New model extraction for predicting distortion in HEMT and MESFET circuits, IEE Microwave and Guided Wave Letters, 9 (9), September 1999, 363-365.

[5] K. Shirakawa, M. Shimizu, N. Okubo and Y. Daido, Structural Determination of Multilayered Large-Signal Neural-Network HEMT Model, IEEE Trans. Microwave Theory and Techniques, 46 (10), October 1998, 1367-1375.

[6] J. Rousset, Y. Harkouss, J. M. Collantes, M. Campovecchio, An accurate neural network model of FET for intermodulation and power analysis, 26th Europ. Microwave Conf., vol. 1 (1996), 16-19.

[7] F.Giannini, G.Leuzzi, G.Orengo, P.Colantonio, "Modeling Power and Intermodulation Behavior of Microwave Transistors with Unified Small-Signal/Large-Signal Neural Network Models," International Journal of RF and Microwave Computer-Aided Engineering, 13 (4), July 2003, 276-284.

[8] S.A. Maas, D. Neilson, Modeling MESFET's for Intermodulation Analysis of Mixers and Amplifiers, IEEE Trans. Microwave Theory and Techniques, 38 (12), December 1990, 1964-1971.

[9] K. Hornik, M. Stinchcombe, and H. White, Universal Approximation of an Unknown Mapping and Its Derivatives using Multilayered Feedforward Networks, Neural Networks, 3 (5), May 1990, 551-560.

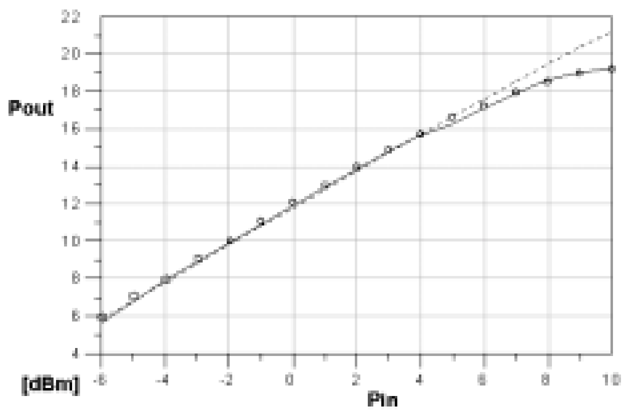


Fig.6. Fundamental power vs input power comparison between measurements (o), large-signal neural model (-) and Volterra series model (--) for Vds=4 V and Vgs=-0.5 V.

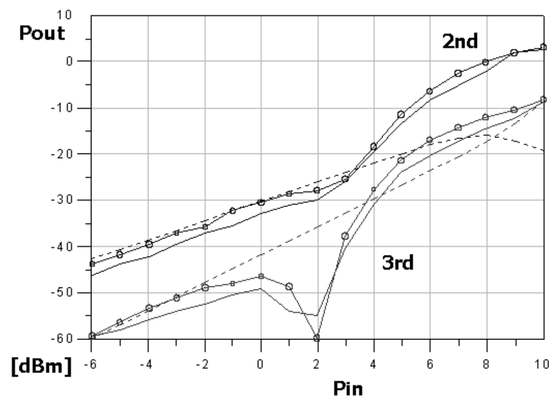


Fig.7. Second and third harmonic power vs input power comparison between measurements (o), large-signal neural model (-) and Volterra series model (--) for Vds=4 V and Vgs=-0.5 V.