Straightforward and Accurate Nonlinear Device Model Parameter-Estimation Method Based on Vectorial Large-Signal Measurements

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***Abstract*—To model nonlinear device behavior at microwave frequencies, accurate large-signal models are required. However, the standard procedure to estimate model parameters is often cumbersome, as it involves several measurement systems (dc, vector network analyzer, etc.). Therefore, we propose a new nonlinear modeling technique, which reduces the complexity of the model generation tremendously and only requires full two-port vectorial large-signal measurements. This paper reports on the results obtained with this new modeling technique applied to both empirical and artificial-neural-network device models. Experimental results are given for high electron-mobility transistors and MOSFETs. We also show that realistic signal excitations can easily be included in the optimization process.**

***Index Terms*—Large-signal measurements, nonlinear modeling, optimization.**

I. Introduction

A RECENT development in microwave metrology is a measurement system that not only enables the measurement of the absolute amplitude of harmonics, and if present, intermodulation products, but also can measure the corresponding phases [1]–[5]. These so-called "vectorial large-signal measurements" have triggered researchers worldwide to investigate the implications of the additional measurement information (being the phase) on the ease and accuracy of nonlinear model generation.

Nonlinear models of microwave devices are commonly described in terms of state functions. These quantities are classically determined via a small-signal detour based on multibias S-parameter measurements. The first investigated approach of using vectorial large-signal measurements in nonlinear modeling was to efficiently extract the device's state functions directly from these measurements [6]. However, the drawback of this extraction method is that the obtained model accuracy is strongly related to the available measurement bandwidth. Therefore, we developed an advanced nonlinear modeling method based on optimization [7]. State functions are typically represented by lookup tables [8], [9] or by parametric models. The latter are characterized by a number of parameters of which the values can be estimated through optimization. As optimization is not suited for lookup tables, this method is not applicable to lookup table models.

Section II describes the straightforward procedure to estimate the parameters of nonlinear device models from vectorial large-signal measurements only. In this study, we apply this method to two types of parametric model types, namely, empirical and artificial-neural-network (ANN) models. Experimental results are presented and analyzed in Section III. Finally, conclusions are drawn in Section IV.

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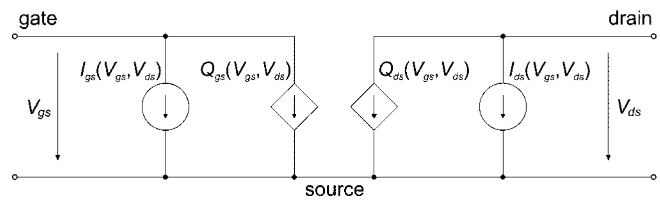

Fig. 1. Intrinsic quasi-static nonlinear FET model.

II. Nonlinear Model Parameter-Estimation Method

A. Optimization Procedure

Fig. 1 represents the nonlinear quasi-static model of an FET, consisting of four state functions. The assumption of quasi-static operation is valid up to the frequencies used in the experiments presented in Section III. Depending on the actually used parametric model, the contributions of the extrinsic elements might or might not be included. If not, they can separately be determined from S-parameter measurements [10], [11].

The classical procedure to determine the parameters of empirical or ANN models is to optimize the functions toward the dc measured state functions, e.g., I_{ds}, and/or toward the S-parameter measurement-based state functions, e.g., C_{gs} or the corresponding large-signal Q_{gs}. Bandler *et al.* [12] proposed, as extension to this procedure, to optimize consistently toward all available measurements, such as dc, multibias S-parameter, and spectrum analyzer data. Obviously, the additional phase information of vectorial large-signal measurements could be incorporated in the optimization procedure. However, this requires special optimization software to ensure consistency because it is not straightforward to implement this method in standard circuit simulators. The reason is that it is not possible to optimize simultaneously toward dc, S-parameter, and harmonic-balance simulations.

Our approach consists of a nonlinear model parameter-estimation procedure based on vectorial large-signal measurements only [7]. Since these measurements provide both amplitude and phase information of the spectral components of the traveling voltage waves, they contain all necessary information. The advantage of this approach is that only one type of measurements, i.e., *in casu* vectorial large-signal measurements, and only one type of simulation, i.e., *in casu* harmonic-balance analysis, are needed. It is even possible to include “dc”- or “S-parameter”-like information by choosing the appropriate operating conditions, e.g., a low input power, when performing the vectorial large-signal measurements.

We have developed this procedure on a measurement setup, i.e., the nonlinear network measurement system (NNMS) [4], which enables to measure simultaneously the currents and voltages at both device ports. The latter implies that the expressions for all four of the state functions can be optimized at once. The first step of the procedure is to perform a number of measurements, called “experiments.” It is possible to sweep any degree of freedom of the measurement system, like input power, excitation frequency, dc bias, load impedance, etc. However, one could focus on particular experiments depending on the ultimate application. Next, the measurement data are stored in Citifile format, which is compatible with the used microwave circuit simulator (ADS, Agilent Technologies). To allow any kind of excitation settings, we take as independent variables the experiment number and frequencies. However, we explicitly save the excitation settings in order to automatically perform the harmonic-balance simulations at the exact operating conditions at which the measurements were performed. Subsequently, the model parameters are estimated during a single optimization process, executed in the circuit simulator environment, in which all the experiments are combined. The optimization goals are expressed in terms of minimizing the difference between the measured and simulated spectral components, taking into account all the significant harmonics and, if present, intermodulation products.

B. Parametric Model Representations

The proposed parameter-estimation method can be applied to both empirical and ANN models. We will evaluate and compare these two approaches in terms of model accuracy and extrapolation properties.

The parameter-estimation procedure is general in the sense that it can be applied to any empirical nonlinear model of a one- or two-port microwave device. To demonstrate the applicability of the method, we used the Chalmers’ empirical nonlinear high electron-mobility transistor (HEMT) model. The expression for the drain–source current $I_{\rm ds}$ is based on [13] and the functions representing the intrinsic bias-dependent capacitances are taken from [14].

Concerning the ANN, it is not the purpose of this study to find the most optimal ANN formulation [15], but to show the principle that the proposed method can be applied to ANNs. We decided not to define one global ANN, but represented each of the four device’s state functions by a separate ANN. The reason is that it is known from device physics that the characteristics of the currents and charges differ significantly and, hence, this can be considered as an *a priori* knowledge-based pruning technique. In this paper, we will show what level of accuracy can be obtained with an ANN consisting of only one hidden layer with five nodes to represent $I_{\rm ds}$ and with three nodes for $Q_{\rm gs}$ and $Q_{\rm ds}$. The gate–source current $I_{\rm gs}$ can be neglected for the experimental conditions presented in Section III. The ANN accuracy can easily be increased by adding additional hidden layers and nodes, but at the cost of a lower model generation speed. The independent input variables are the terminal voltages $V_{\rm gs}$ and $V_{\rm ds}$. The functional description is of the form

$$I_{\rm ds},\, Q_{\rm gs},\, Q_{\rm ds} = \sum_{i=1}^{Q} \left[w_i \tanh\left(v_{i1} V_{\rm gs} + v_{i2} V_{\rm ds}\right) + c_i \right] \quad (1)$$

where Q is the number of nodes and where w_i, v_{i1}, v_{i2}, and c_i are the parameters to be determined. We choose this particular functional description because the $\tanh(.)$ is smooth and its limits are well defined. This is contrary to an exponential-like expression, which might give rise to convergence problems when the nonlinear model is being evaluated by the iterative harmonic-balance analysis. The ANN training was not performed in a separate software program, but was also executed by the optimizer available in the circuit simulator.

III. Experimental Results

To illustrate the parameter-estimation procedure, we present and analyze experimental and modeling results on transistors fabricated with different technologies and excited at several operating conditions.

The first example is the Chalmers model applied to a GaAs pseudomorphic high electron-mobility transistor (pHEMT). The device is operated in class B, while the input power is swept from -20.4 to -3.4 dBm. All the model parameters are simultaneously optimized toward these measurements. Fig. 2 compares the measured and simulated time-domain waveform of $I_{\rm gs}(t)$ [see Fig. 2(a)] and of $I_{\rm ds}(t)$ [see Fig. 2(b)] as a function of the corresponding time-domain waveform of $V_{\rm gs}(t)$ at a high input power. This figure clearly shows a very good agreement between measurements and modeling results and, hence, indicates a high model accuracy.

Fig. 3 shows excellent agreement between the measured and modeled $I_{\rm ds}(t)$ versus $V_{\rm gs}(t)$ by applying the ANN model to an nMOS transistor operated in class A. This example demonstrates that the proposed procedure is not limited to HEMTs, but applicable to one- and two-port nonlinear microwave devices in general.

Furthermore, complicated and realistic operating conditions can easily be included in the optimization procedure. Examples are load–pull measurements [7] and two-tone excitations. The latter is demonstrated on an InP lattice-matched (LM) HEMT. A single-tone continuous wave (CW) signal a_1 is applied to the gate and a single-tone CW signal a_2 at a different fundamental frequency is applied to the drain. Fig. 4 compares the measured $I_{\rm ds}(t)$ with the Chalmers model results and ANN results, respectively. Both model types represent the modulated $I_{\rm ds}(t)$ well.

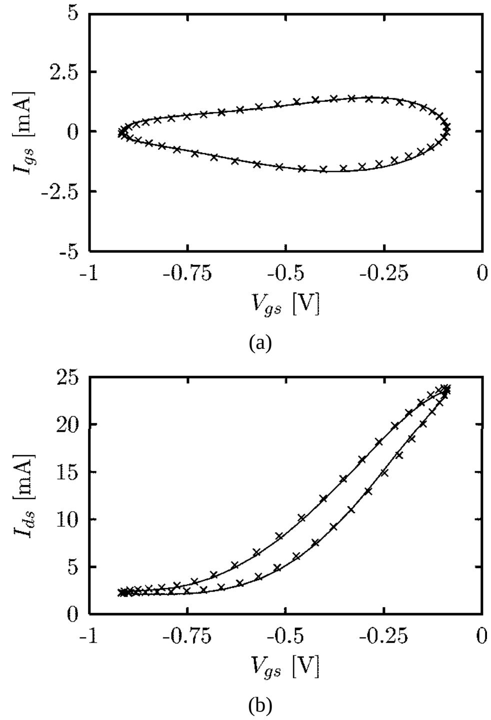

Fig. 2. Measured (×) and Chalmers modeled (—) (a) $I_{\rm gs}(t)$ and (b) $I_{\rm ds}(t)$ versus $V_{\rm gs}(t)$ of a 0.2 μm × 100 μm GaAs pHEMT ($V_{\rm gsDC} = -0.5$ V, $V_{\rm dsDC} = 1.5$ V, $f_0 = 3.6$ GHz, $P_{\rm in} = -3.4$ dBm).

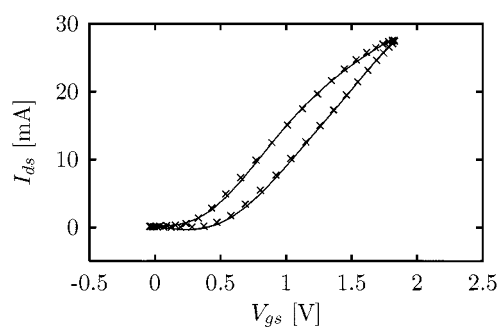

Fig. 3. Comparison of the measured (×) and neural-network modeled (—) $I_{\rm ds}(t)$ versus $V_{\rm gs}(t)$ of a 0.2 μm × 50 μm nMOS ($V_{\rm gsDC} = 0.9$ V, $V_{\rm dsDC} = 1.8$ V, $f_0 = 0.9$ GHz, $P_{\rm in} = 3.4$ dBm).

There is no significant difference in model accuracy between the Chalmers model and the limited-size ANN.

Fig. 5 presents the results of both the Chalmers and ANN models when extrapolated toward a dc-bias condition that was not included in the optimization. We notice that the Chalmers model is able to represent very well the device's characteristics at this particular operating condition. On the contrary, the ANN only approximates the general behavior. The reason is that the ANN is a black-box model and, therefore, not suited for extrapolation. It will, however, behave well at operating frequencies different from the frequencies used in the training process since the ANN definition (see Section II-B) explicitly makes the distinction between charge and current sources. The extrapolation capability of the Chalmers model toward other dc biases is significantly better since the underlying equations are related to the device physics. By including operating conditions closer to the one used in Fig. 5, the accuracy of the ANN model improves.

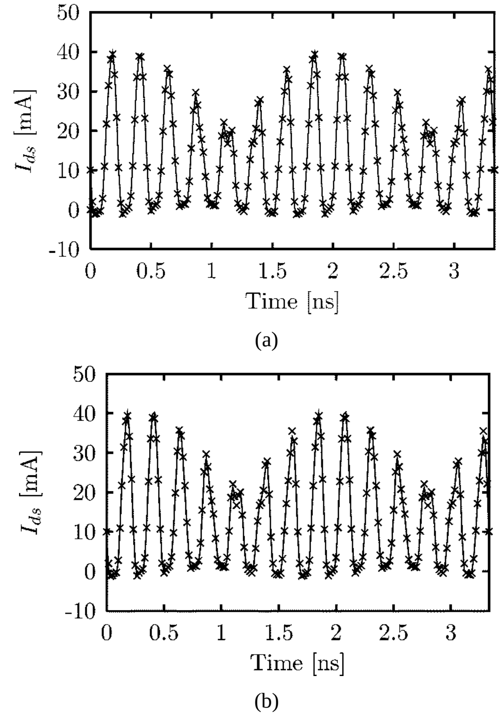

Fig. 4. Comparison of the measured (×), (a) Chalmers (—), and (b) ANN modeled (—) $I_{\rm ds}(t)$ of a 0.2 μm × 100 μm InP LM HEMT excited by a two-tone signal ($V_{\rm gsDC} = -0.1$ V, $V_{\rm dsDC} = 1.2$ V, $f_{0,1} = 4.2$ GHz, $f_{0,2} = 4.8$ GHz, $a_1 = -3.9$ dBm, $a_2 = 2.4$ dBm, $\phi(a_2) - \phi(a_1) = -95°$).

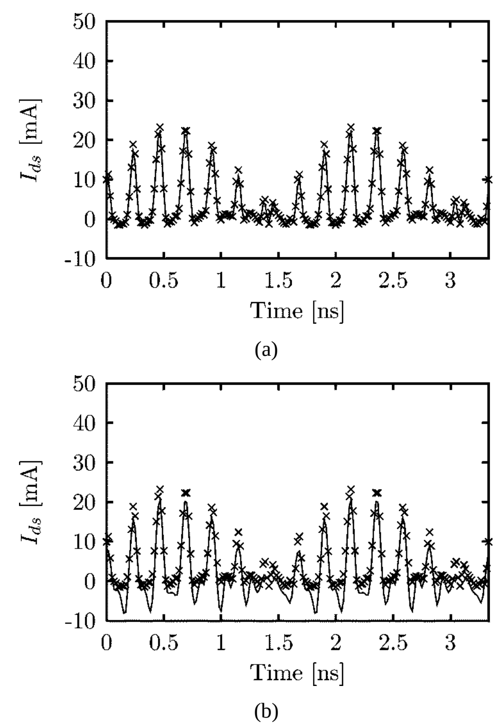

Fig. 5. Comparison of the measured (×), (a) Chalmers (—), and (b) ANN extrapolated (—) $I_{\rm ds}(t)$ of a 0.2 μm × 100 μm InP LM HEMT excited by a two-tone signal ($V_{\rm gsDC} = -0.3$ V, $V_{\rm dsDC} = 0.6$ V).

When there is interest to increase the accuracy and operating range to be covered, ANNs have the advantage that it is straightforward to increase the number of hidden layers and nodes in order to obtain these goals. In the case of empirical models, the number of parameters is mostly fixed and possible extensions are limited. The consequence is that the obtained accuracy is strongly related to the physical phenomena described by the empirical expressions. Therefore, extrapolations toward "smooth" operating conditions will, in general, yield good results, but extrapolations toward "extreme" operating conditions will be worse.

Finally, the parameter-estimation time depends on the software used, but this is, in general, less for empirical models. Typically, an empirical model has significantly less model parameters than an ANN, e.g., 18 compared to 44 for the modeling results presented in this paper.

It is clear that the choice between an empirical model or an ANN strongly depends on the envisaged application.

IV. Conclusions

We have shown that using only full two-port vectorial large-signal measurements is sufficient to accurately estimate the parameters of nonlinear microwave device models. The developed straightforward quasi-automatic procedure has been applied to empirical and ANN models, and has been successfully demonstrated on HEMTs and nMOS devices. Finally, we pointed out that including realistic operating conditions in the optimization process broadens the model validity range.

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