Neural-Based Large-Signal Device Models Learning First-Order Derivative Parameters for Intermodulation Distortion Prediction

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A detailed procedure to learn a nonlinear model together with its first-order derivative data is presented. Two correlated multilayer perceptron (MLP) neural networks providing the model and its first-order derivatives, respectively, are trained simultaneously. Applying this method to FET devices leads to nonlinear models for current and charge fitting derivative parameters. The training data is the bias-dependent equivalent circuit parameters extracted from S-parameter measurements. The resulting models are suitable for both small-signal and large-signal analyses, in particular for intermodulation distortion prediction. Examples for power amplifier simulations of power transfer, efficiency and intermodulation distortion performances are presented.

INTRODUCTION

The standard approach for characterizing an integrated microwave device and its enclosing package requires the extraction of an equivalent circuit which is fitted to electrical measurements. Neural networks have been usefully applied to model the bias dependence of S-parameters and output current to perform small-signal and large-signal models, respectively (1). CAD software systems generally implement separate small-signal and large-signal models. However, this can lead to inconsistent simulation results.

To overcome this problem, neural networks can be used to learn a model using not only input/output data but also derivative data. If two neural networks, one providing the model to learn and an adjoint network modelling its derivative parameters, have correlated architectures, can learn both models simultaneously (2,3). In this paper a practical implementation providing modifications of the backpropagation training algorithms is presented.

The proposed approach is applied to find large-signal models for drain current and charge in FET devices without loss of generality. An experiment based on a 0.5x1000µm medium power GaAs MESFET is presented. The process is implemented by the AMS foundry (Alenia-Marconi Systems).

The training data is the bias-dependent equivalent circuit parameters extracted from S-parameter measurements. Notice that learning the equivalent circuit parameters means learning the derivative information of the large-signal model. The capability of training an active device model, using the first-order derivative information, is very useful in simultaneous small-signal/large-signal device simulation, and allows intermodulation distortion prediction.

NEURAL NETWORK APPROACH

Consider the MLP neural network shown in Figure 1, modelling the I_{ds} current of an FET device as a function of the bias voltages V_{gs} and V_{ds}. First-order derivative parameters G_m and G_{ds} can be modeled by an adjoint neural network shown in Figure 2. The same number of layer 1 neurons in both networks must be chosen to obtain the required accuracy. F is the nonlinear transfer function.

The two networks have correlated weights and topologies. In order the two networks to be trained simultaneously, a global network has to be built. On account of weight and bias correlations, constraints on derivative calculation must be imposed in the backpropagation algorithm used to train the network.

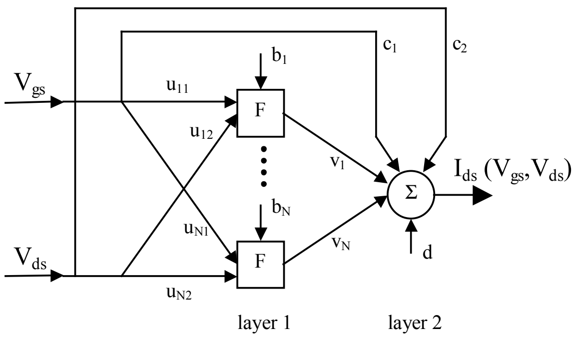


Figure 1: A two layer neural network modelling the I_{ds} current.

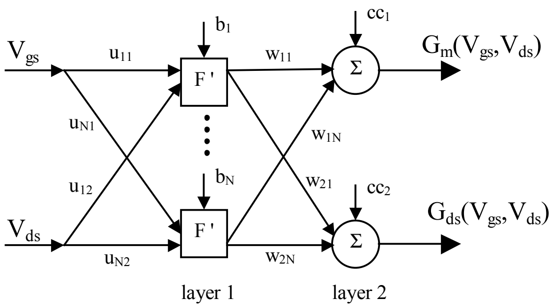


Figure 2: An adjoint neural network modelling I_{ds} first-order derivative parameters.

The global network can be trained alternatively with the only input/output data of the function to learn, with only its derivative data, or finally, with both of them. In every case the network will provide both the function and its derivative models as well.

FET LARGE-SIGNAL MODEL

The proposed technique has been applied to find a large-signal model of a FET device. In particular a 0.5x1000μm medium power GaAs MESFET implemented by the AMS foundry (Alenia-Marconi Systems) has been considered.

The bias-dependent intrinsic parameters, from the extracted small-signal equivalent circuit shown in Figure 3a (4), provide nonlinar current and charge partial derivatives, corresponding to the nonlinear equivalent circuit shown in Figure 3b

$$G_m = dI_{ds}/dV_{gs} \qquad G_{ds} = dI_{ds}/dV_{ds}$$

$$C_{11} = dQ_g/dV_{gs} \qquad C_{12} = dQ_g/dV_{ds}$$
$$C_{21} = dQ_d/dV_{gs} \qquad C_{22} = dQ_d/dV_{ds}$$

where derivative capacitances are defined from intrinsic capacitances as (5,6)

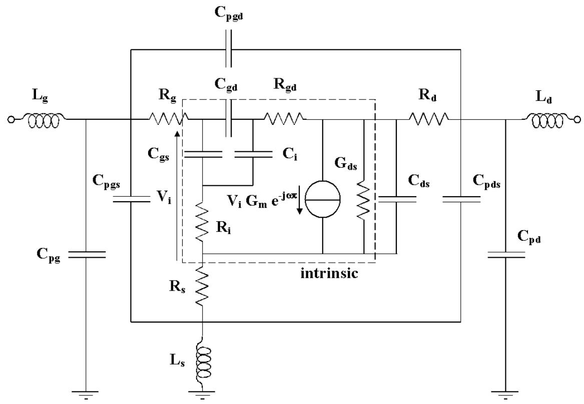
$$C_{11} = C_{gs} - C_{gd} \qquad C_{12} = C_{21} = -C_{gd}$$

and

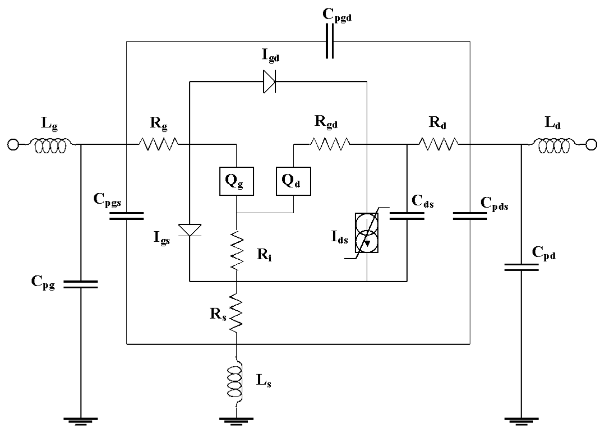
$$C_{22} = C_{ds} - C_{gd}$$

The nonlinear relationship of I_{ds}, Q_g and Q_d with respect of large-signal voltages V_{gs} and V_{ds} are each evaluated by mean of a couple of neural networks as that shown in Figure 1 and Figure 2. The nonlinear transfer function chosen for the two sub-networks are the hyperbolic tangent and its first-order derivative, respectively.

The I_{ds} model is extracted training the first-order derivative sub-network with the extracted parameters G_m and G_{ds}. Input/output training data for the I_{ds} sub-network are taken from DC measurements, especially to impose deep pinchoff and zero-crossing constraints to the I-V characteristics. DC current data, on the other hand, have a wrong RF behavior, especially for the output conductance. The result, which is plotted in Figure 4, is that the I_{ds} model will be completely defined for any input voltage, whereas traditional I_{ds} models need conditional statements to separate different voltages domains. This fact speed up nonlinear simulations involving different bias regions.



(a)



(b)

Figure 3: MESFET (a) linear and (b) nonlinear equivalent circuit

On the other hand, to train charge models from C_{ij} parameters, only derivative data is available, that is only the derivative sub-network is trained, whereas the Q_g and Q_d sub-networks provide the desired charge models. After training, a good agreement of equivalent circuit parameters between the neural models and experimental data is observed at all the 100 bias points, as it can be seen in Figg.5-6. Neural models for gate-source current I_{gs} and gate-drain breakdown current I_{gd} have been also trained on DC current measurements.

EXPERIMENTAL RESULTS

The five neural models have been easily implemented into a user-defined nonlinear device model of the Agilent ADS microwave circuit simulator to predict the performance at 5 GHz of the power amplifier shown in the circuit schematic of Figure 7. The results for power gain and power transfer are shown in Figure 8 and 9 respectively, whereas a prediction of power efficiency is shown in Figure 10. Acceptable approximation of third-order intermodulation (IMD3) behavior with two tones at 5 GHz and 5.05 GHz has been also obtained and results are plotted in Figure 11.

CONCLUSIONS

A detailed procedure to learn nonlinear models using also derivative information has been presented. When applied to large-signal parameter extraction of nonlinear devices, using only first-order derivative information, this approach has led to models that have the same complexity of traditional formula-based models but are more consistent and reliable, both for small-signal and large-signal behavior prediction. The simulation of a power amplifier circuit with the neural FET models approaches the accuracy of the measured data.

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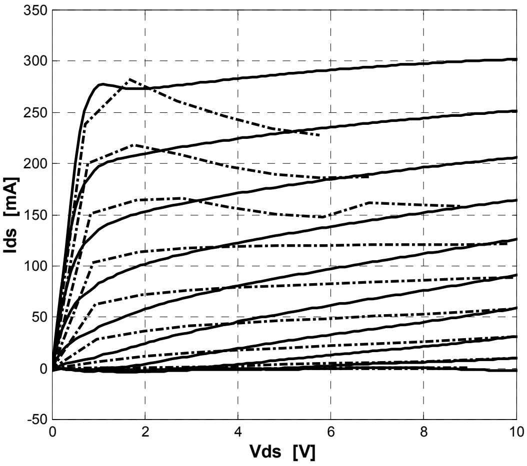

Figure 4: I_{ds} neural model curves (continuous) and DC measured curves (dashed).

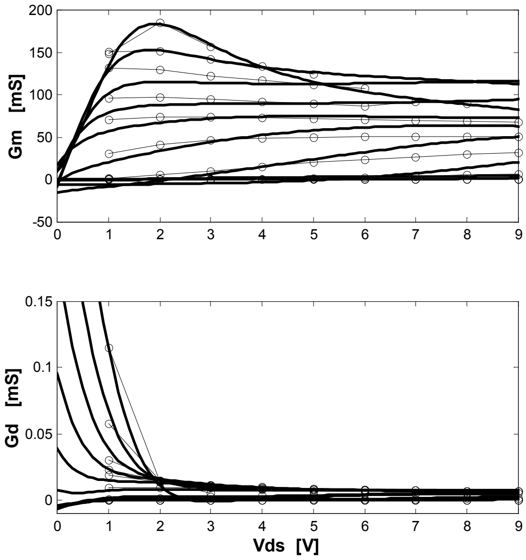

Figure 5: Ids first-order derivative model fitting.

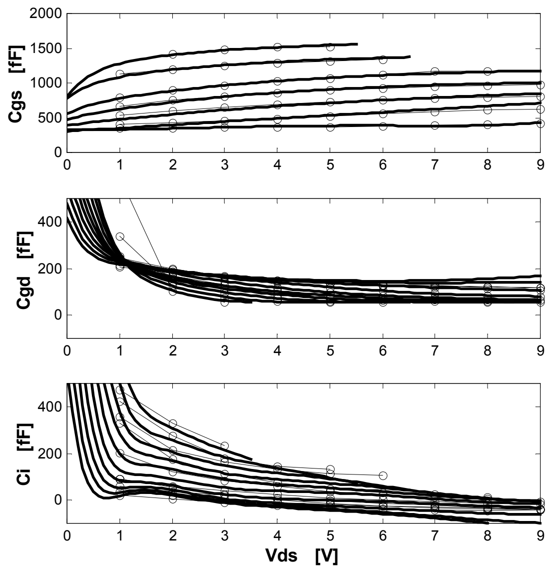

Figure 6: Charge derivative model fitting

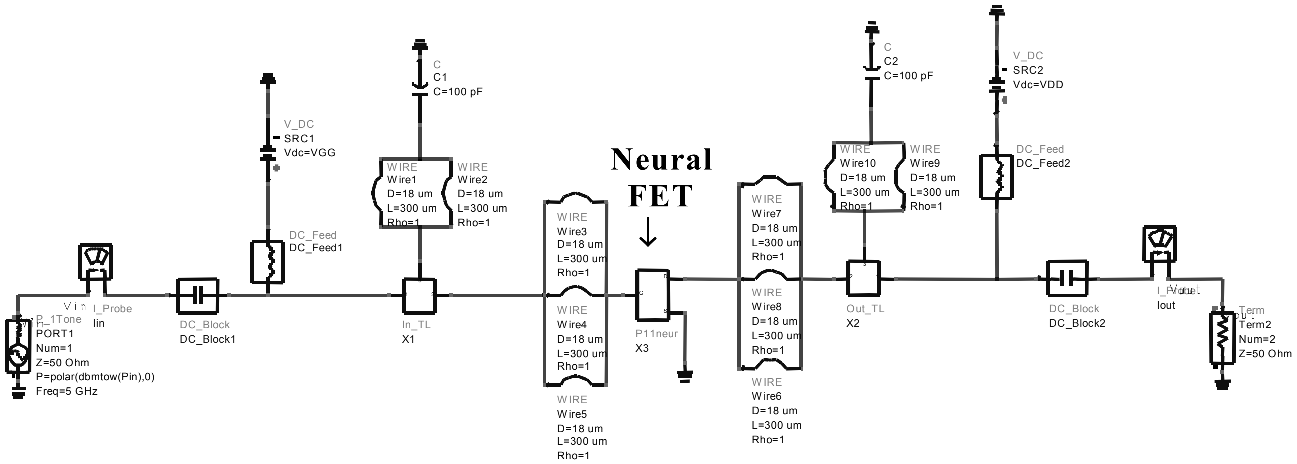

Figure 7: Agilent ADS power amplifier simulation circuit.

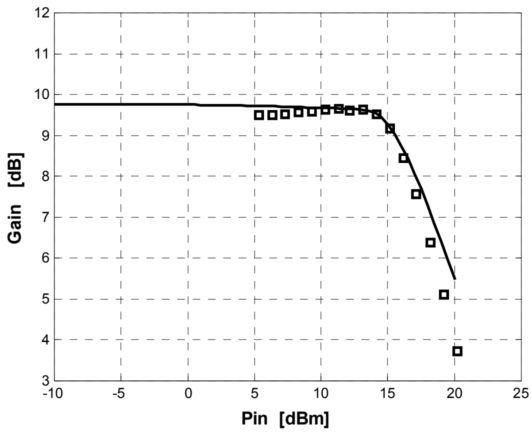

Figure 8: Power amplifier gain simulation and measurements.

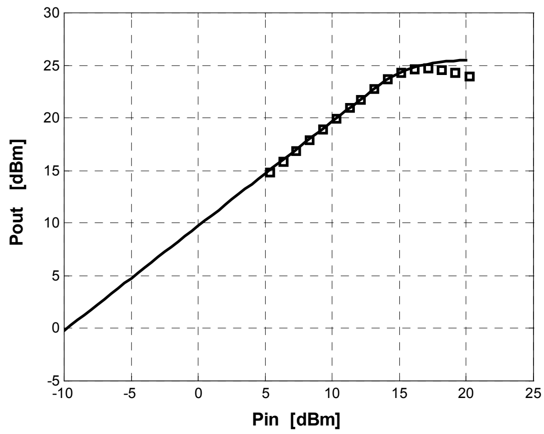

Figure 9: Amplifier power transfer simulation and measurements.

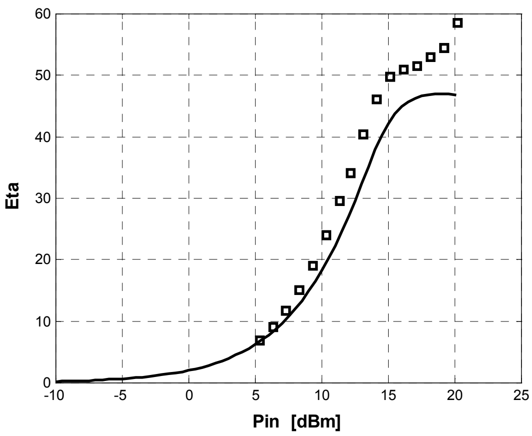

Figure 10: Amplifier power efficiency simulation and measurements.

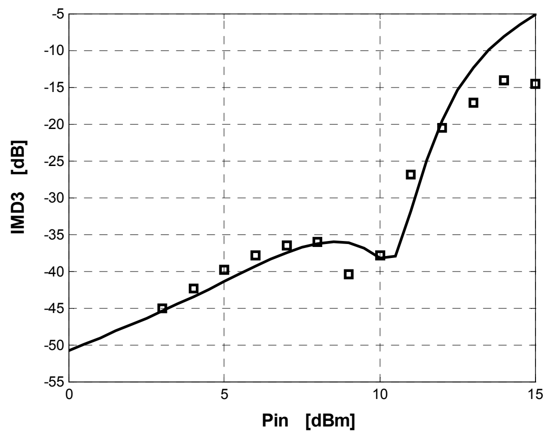

Figure 11: IMD3 simulation and measurements.