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Modeling the Drain Current of a PHEMT using the Artificial Neural Networks and a Taylor Series Expansion

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ABSTRACT: Artificial neural networks (ANNs) have recently been introduced in the microwave area as a fast and flexible vehicle to microwave modeling, simulation and optimization. The models are fast and can represent EM/physics behaviors it learnt which otherwise are computationally expensive. In this paper a neural network model is developed for a Pseudomorphic High Electron Mobility Transistor PHEMT (ED02AH-6x30), a transistor of 6 gate fingers, each with a width of 30 µm .An multi-layer perceptron (MLP) structure is used to model the nonlinear I-V characteristics, using a data measurement and the back propagation algorithm with adaptive learning rate and momentum for the training process. The final results are compared with data measurement and a good agreement is obtained between model and data. The accurate model will be used finally to obtain a small signal model for the drain current using the Taylor series expansion.

KEYWORDS: Neural networks, multi-layer perceptron, back propagation algorithm, PHEMT, Taylor series expansion.

1 INTRODUCTION

Microwave transistors (MESFETs, HEMTs, PHEMT and HBTs) are used in majority of devices in modern microwave communication systems (satellite systems, mobile systems, radio-relay, etc.). Development of accurate and reliable models of microwave transistors is one of the basic aspects in design of circuits containing these transistors.

Different equation-based empirical large-signal models have been proposed for the simulation of field effect transistors (FETs) in nonlinear microwave circuits like amplifiers, filters, mixers and multipliers. The majority of empirical models based on empirical measurements to extract the parameters. For GaAs MESFET Curtice, Statz, Materka models are the most used in simulators [1] [2]; many good models have been developed for HEMT and PHEMT devices [3] [4]. However, the existing models with closed-form equations, while good for many existing devices, may not fit well with new devices.

Neural networks, also called artificial neural networks (ANNs), are information processing systems with their design inspired by the studies of the ability of the human brain to learn from observations and to generalize by abstraction. The fact that neural networks can be trained to learn any arbitrary nonlinear input–output relationships from corresponding data has resulted in their use in a number of areas such as pattern recognition, speech processing, control, biomedical engineering etc. Recently, ANNs have been applied to RF and microwave computer-aided design (CAD) problems as well [6] [7] [8] [9].

Artificial neural networks (ANNs) have been in use to replace empirical equations or compact models for a variety of devices such as MESFFT, HEMT and PHEMT [10] [11] [12] [13] [14]. These models are based on an equivalent circuit and require less time for their development compared to compact models and offers many advantages:

- Neural networks can “learn” form measured device data, allowing model development, even when formulae are unavailable.
- ANN based model is simple to extract, easy to build and fast to evaluate.

In this paper a neural network model is developed for a Pseudomorphic High Electron Mobility Transistor PHEMT (ED02AH-6x30), a transistor of 6 gate fingers, each with a width of 30 µm .An multi-layer perceptron (MLP) structure is used to model the nonlinear I-V characteristics, using a data measurement and the back propagation algorithm with adaptive learning rate and momentum for the training process. Once the neural network is trained, the drain current can be writing as a mathematical function. The Taylor series coefficients can be extracted by differentiating the ANN mathematical expression as it is n times derivable. The accurate model will be used finally to obtain a small signal model for the drain current.

2 MODELING TECHNIQUE

2.1 MLP NEURAL NETWORK STRUCTURE

A standard multilayer perceptron (MLP) as shown in fig.1 consists of an input layer (layer 1), an output layer (layer N_L) and as well as several of hidden layers [6] [7] [8].Input vectors are presented to the input layer and fed through the network that then yields the output vector. The lth layer output is:

$$z_i^l = \varphi\left(\sum_{j=0}^{N_{l-1}} w_{ij}^l z_j^{l-1}\right) \qquad (1)$$

Where: $l = 2,3,\ldots,L$ and $i = 1,2,3,\ldots,N_l$

Where z_i^l and $z_i^{l-1}$are outputs of lth and (l-1)th layer, w_{ij}^l are the weights between the ith neuron in the lth layer and the jth neuron in the (l-1)th layer. The function φ is an activation function of each neuron, the linear function is used in output layer, and sigmoid in hidden layers, the sigmoid is defined as:

$$\varphi(x) = \frac{1}{1+e^{-x}} \qquad (2)$$

The neural network learns relationship among sets of input output data (training sets).First, input vectors are presented to the input neurons and output vectors are computed. These output vectors are then compared with desired values and errors are computed. The training process proceeds until errors are lower than the prescribed values or until the maximum number of epochs (epoch is the whole training set processing) is reached. Once trained, the network provides fast response for various input vectors (even for those not included in the training set) without additional optimizations. Usually, neural networks with different number of hidden neurons are trained, tested and after their comparison, the network with the best modeling results is chosen as the neural model [6] [7].

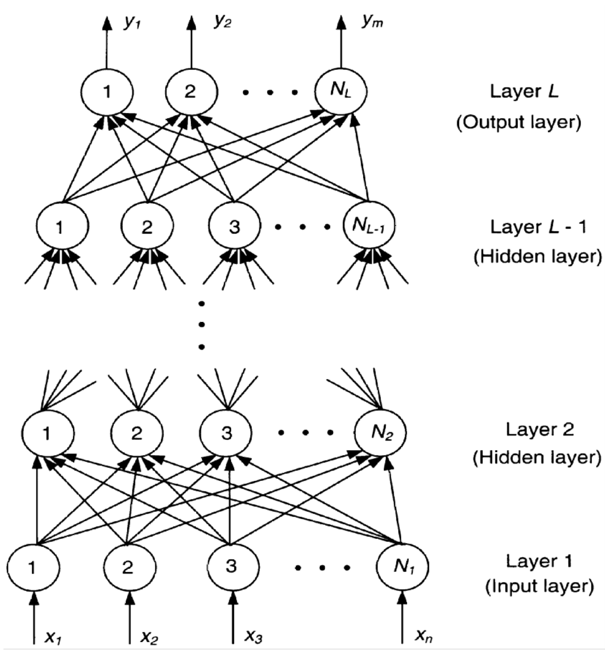


Fig. 1. Multi-layers perceptron (MLP) structure

2.2 THE TAYLOR SERIES EXPANSION OF THE DRAIN CURRENT OF PHEMT

The nonlinear small-signal drain current $\mathrm{I_d}$ depends on both the drain-to-source and gate-to-source bias point $(\mathrm{V_{d0}}, \mathrm{V_{g0}})$ and the drain-to source and gate-to-source dynamic voltages over the bias point$(\mathrm{v_d}, \mathrm{v_g})$. Around a fixed operating point (V_{d0}, V_{g0}) the voltages V_d and V_g can be written as:

$$V_d = V_{d0} + v_d \quad (3.a)$$

$$V_g = V_{g0} + v_g \quad (3.b)$$

The drain current I_d is a function of $(V_{d0}, V_{g0}, v_d, v_g)$:

$$I_d = I_{d0} + i_d = f\left((V_{d0}, V_{g0}, v_d, v_g)\right) \quad (3.c)$$

If the input excitation is small enough, $\mathrm{I_d}$ can be represented in a small interval around the bias point by the following two dimensional truncated Taylor series expansion:

$$I_d(V_d, V_g) = I_{d0} + G_m v_g + G_d v_d + G_{m2} v_g^2 + G_{md} v_g v_d + G_{d2} v_d^2 + G_{m3} v_g^3 + G_{m2d} v_d^2 v_d + G_{md2} v_g\, v_d^2 + G_{d3} v_d^3 \qquad (3.d)$$

WhereI_{d0} is the DC current and $G_m\,, G_d \ldots G_{md2}$ are coefficients related to the n^{th}order derivatives of the I-V characteristic with respect to the instantaneous voltages evaluated at the bias point [15].

$$G_m = \left.\frac{\partial I_d(V_d, V_g)}{\partial V_g}\right|_{V_g=V_{g0};V_d=V_{d0}} \quad ; G_{m2} = \left.\frac{1}{2}\frac{\partial^2 I_d(V_d, V_g)}{\partial^2 V_g}\right|_{V_g=V_{g0};V_d=V_{d0}} \quad ; G_{m3} = \left.\frac{1}{6}\frac{\partial^3 I_d(V_d, V_g)}{\partial^3 V_g}\right|_{V_g=V_{g0};V_d=V_{d0}}$$

$$G_d = \left.\frac{\partial I_d(V_d, V_g)}{\partial V_d}\right|_{V_g=V_{g0};V_d=V_{d0}} \quad ; G_{d2} = \left.\frac{1}{2}\frac{\partial^2 I_d(V_d, V_g)}{\partial^2 V_d}\right|_{V_g=V_{g0};V_d=V_{d0}} \quad ; G_{d3} = \left.\frac{1}{6}\frac{\partial^3 I_d(V_d, V_g)}{\partial^3 V_d}\right|_{V_g=V_{g0};V_d=V_{d0}}$$

$$G_{md} = \left.\frac{\partial^2 I_d(V_d, V_g)}{\partial V_g \partial V_d}\right|_{V_g=V_{g0};V_d=V_{d0}} \quad ; G_{m2d} = \left.\frac{1}{2}\frac{\partial^3 I_d(V_d, V_g)}{\partial^2 V_g \partial V_d}\right|_{V_g=V_{g0};V_d=V_{d0}} \quad ; G_{md2} = \left.\frac{1}{2}\frac{\partial^3 I_d(V_d, V_g)}{\partial^2 V_d \partial V_g}\right|_{V_g=V_{g0};V_d=V_{d0}} \qquad (3.e)$$

3 THE PROPOSED STRUCTURE AND TRAINING PROCESS

A multilayer (MLP) Neural network perceptron is used to modeling the current drains Id, whose input are Vgs and Vds.The back propagation algorithm with adaptive learning rate and momentum is used for the training process. After training and evaluation of the networks with different number of hidden neurons, a network with tow hidden layers consisting of 5 neurons for each one give the best results, obtaining a good model requires 361 steps (Vds (0V to 5V) and Vgs (-2V to 0.6V)). The relative error for each training sample is given in the fig 2 and the table 1 gives performances of the neural model.

Table 1. Neural model performances

Maximum absolute error	Average absolute error	Average relative error
0.57 mA	0.28 mA	0.6%

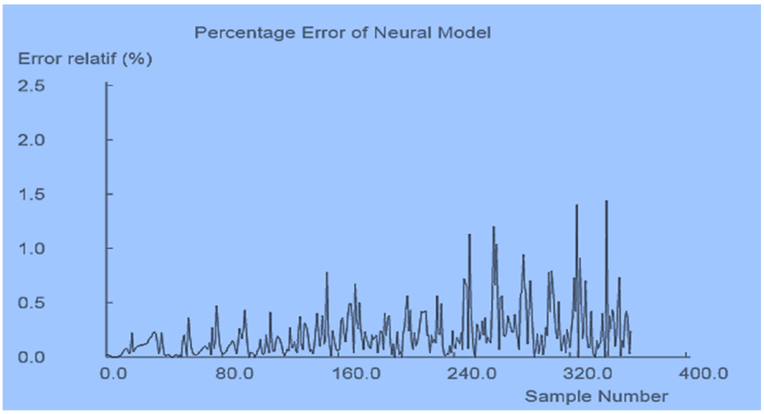


Fig. 2. Relative error for each training sample

4 RESULTS

The model is tested and compared with measurement for deferent valor's of V_{ds} and V_{gs}. Very good agreement can be observed at fig 3.

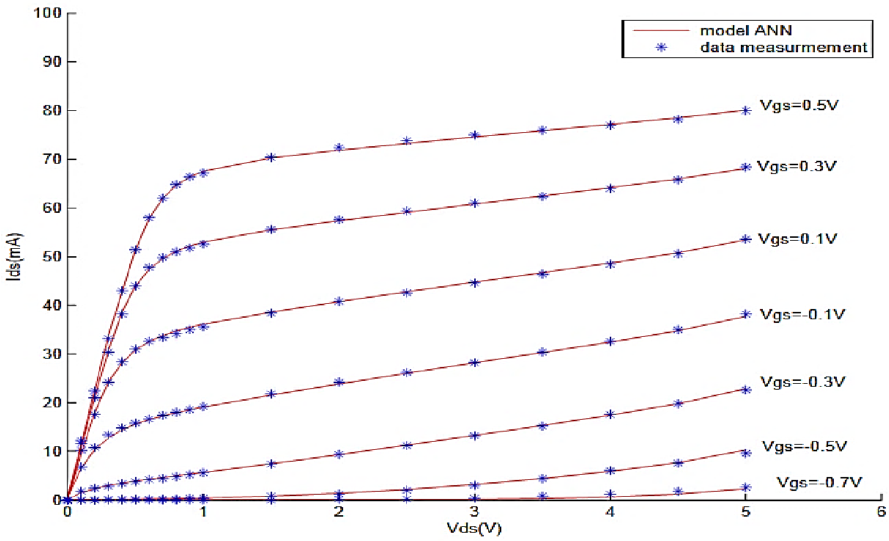


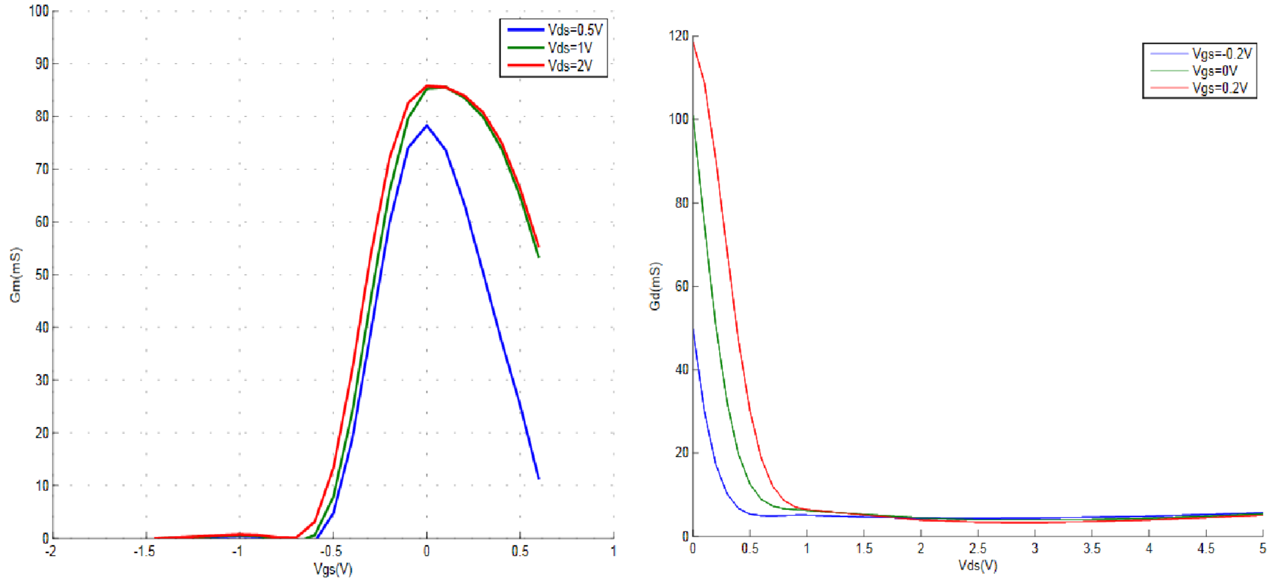
Fig. 3. PHEMT drain-current comparison between ANN model and measurement data.

Once the neural network is trained, the drain current can be writing as a mathematical function. The Taylor series coefficients can be extracted by differentiating the ANN mathematical expression as it is n times derivable. The Figure 4 shows the variation of $G_m$and G_d as function of V_{ds} and V_{gs}. While the results obtained for G_m and G_d are compared with values obtained by extraction from measured S-parameters, such as shown in Figure 5.

The Taylor series expansion can be deduced for each bias point and we can predict the behaviors of the drain current source in the small-signal situation.

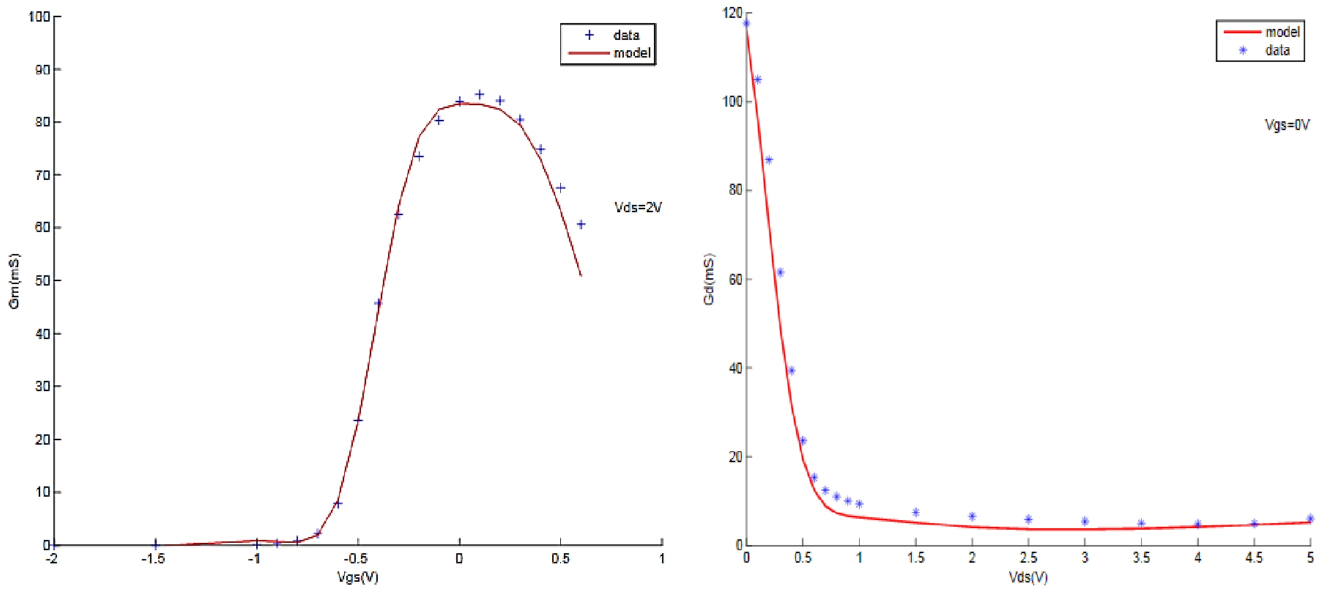
As an example, for $\left(V_{d0} = 2V, V_{g0} = -0.2V\right)$ we have:

$I_{d0} = 16.0441mA$; $G_m = 75.3960mS$; $G_d = 4.3436mS$; $G_{m2} = 58.6097mA.V^{-2}$; $G_{m3} = -71.7296\ mA.V^{-3}$; $G_{d2} = -0.1045mA.V^{-2}$; $G_{d3} = 0.0793mA.V^{-3}$; $G_{md} = 4.9209mA.V^{-2}$; $G_{m2d} = -15.355\ mA.V^{-3}$; $G_{d2m} = -1.508mA.V^{-3}$



(a) *(b)*

Fig. 4. ***(a) the transconductance G_m and (b) the output conductance G_d provided by the proposed ANN model***



(a) *(b)*

Fig. 5. ***(a) the transconductance Gm and (b) the output conductance Gd compared with values obtained by extraction from measured S-parameters***

5 CONCLUSION

An MLP structure has proposed for modeling the drain-current of a PHEMT using the back propagation algorithm with adaptive learning rate and momentum for the training process. Good agreement is obtained between model and data measurement. The ANN model mathematical expression is used to obtain the analytical expression of the transconductance, output conductance and all Taylor series coefficients. The behaviors of the drain current source in the small-signal situation are finally modeled by using a Taylor series expansion that can be used in a simulator environment as an accurate and fast model.

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