# Nonlinear Modeling of Si/SiGe HBT Using ANN

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*Abstract* — **We present a large signal model for Si/SiGe HBTs using an Artificial Neural Network (ANN). The ANN is used to model the DC non-linearities of the intrinsic device. In this way, physical phenomena such as nonideal leakage currents and the Kirk effect can be modeled without time-consuming extraction. Capacitive nonlinearities are modeled by the well-known relationship between the capacitance and the junction voltage, ignoring the diffusion capacitance. By comparing ANN model results to measurements, we show that a good agreement for DC and nonlinear characteristics is obtained.**

## I. INTRODUCTION

There is a high demand for Si/SiGe HBTs in the area of Si-based microwave MMICs due to their superior high frequency performance [1]. For the design of non-linear circuits such as oscillators and power amplifiers, a non-linear model needs to be developed. The most common models for HBTs are compact models such as VBIC, HICUM, and MEXTRAM. The general drawback of compact models is the difficulty to extract their parameters, as many kinds of measurements and setups are required for this purpose. The alternative modeling approach are equivalent scheme models. In [2], the authors extend a small-signal equivalent circuit model to incorporate nonlinearities arising from the base-emitter (B-E) junction and from the collector current source. They used a well known diode current equation to represent the resistive current of (B-E) junction and Taylor expansion to model both of the capacitive part of the (B-E) junction and the collector current source. We modify this work by using the ANN representation instead of the diode equation to model the DC resistive current of the B-E junction and instead of approximated Taylor expansion to model the collector current source, and this as function of both terminal voltages $V_{BE}$ and $V_{CE}$. This approach has many advantages: firstly, the ANN can closely approximate the nonlinear function and its derivatives (responsible of non-linear behavior of the device)[3]. Secondly, ANN has a sigmoid basis function that can represent well the shape of the device nonlinearities and that is less prone to convergence problems than polynomials. Thirdly, it is a more physical approach, as example the Early effect is taken into account via the $V_{CE}$ dependency. Fourthly, we have not to extract the physical parameters of the device like saturation current $I_0$ or $\eta$ the ideality factor of the (B-E) junction or $\beta$ current gain factor Finally, the ANN model is very easy to build. The capacitive non-linearity remains formulated using the classical capacitance-voltage junction relationship in reverse bias, and by linear extrapolation in the forward region, its parameters extracted by iterative method. The diffusion part of the B-E capacitance is not taken into account, as the junction part dominates [2].

The paper is organized as follows: First, the extraction of the small-signal elements is summarized in Section II. Then, we show the theory of A.N.N in section. III, the proposed non-linear large-signal model is covered in section IV. Model validation is presented in section V. Finally the conclusions are drawn in Section VI.

## II. SMALL SIGNAL MODELING OF THE DEVICE

The first step in the modeling procedure is the extraction of the small-signal equivalent scheme. The complete scheme as seen from the probe tips can be subdivided into two parts: the intrinsic core of the device and the external parasitics as shown in Fig. 1. Details of our extraction procedure can be found in [4]. The extrinsic elements are determined by measuring open, short, and pad dummy structures. The values are used to de-embed the measurements carried out using both DC which used to build the model (sec. IV) and LSNA which used to validate the model (sec. V). The intrinsic circuit shown in Fig.2 contains 9 elements, i.e., one additional element '$C_f$' over the models found in literature, in order to model the base distributed effect through $C_f$ and $C_{bc}$. In this way, current crowding phenomena are incorporated. The intrinsic elements values are determined by means of a random search algorithm.

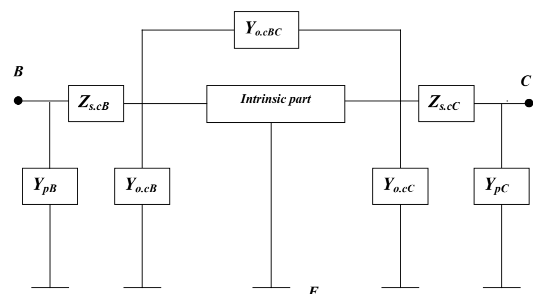


Fig. 1. Representation of the SiGe HBT in the measurement configuration. The actual transistor is represented by the rectangle called 'intrinsic transistor'. The series impedances and parallel admittances model the probe pads and access transmission lines.

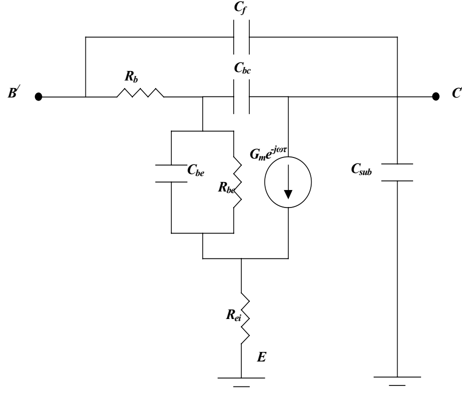


Fig. 2. Intrinsic small-signal model

## III. ARTIFICIAL NEURAL NETWORK

In this Section, the concept of artificial neural networks is briefly reviewed to support the proposed model development in Section IV.

ANN is a mathematical tool to represent the nonlinear relationship between a set of input and a set of output data. In general, due to its architecture and choice of base functions, an ANN model suffers less from convergence problems than the alternative multi-dimensional polynomial. The architecture is shown in Fig. 3. Its basic representation consists of three layers: the input layer, one hidden layer, and the output layer. The input layer represents the input variables, e.g., the DC bias voltages. The output layer represents the output variables, e.g., the DC currents. The relationship between the input and output variables is modeled by means of one or more hidden layers, with each having some number of hidden neurons. The base functions are called 'activation functions'. There are different kinds of ANNs according to the type of the used activation function, namely Multi-Layer Perceptron (MLP), the Radial Basic Function (RBF), and the rational neural network. In this work, we adopt the three-layer MLP architecture with the sigmoid as base function.

The ANN is constructed through learning from a set of input/output data (training set). The used training algorithm is the back-propagation algorithm [5], as implemented in the Neuro-Modeler program [6]. After training, the ANN is able to generalize the relationship between the input and output, in the sense that for a given input value, which is not in the training set, it can predict the corresponding output.

The mapping between the input vector $x$ with $N_x$ the number of input neurons, and the output vector $y$ with $N_y$ the number of output neurons, can be determined as follows:

The inputs to the hidden layer are the $\gamma_k$, calculated from the input variables by:

$$\gamma_k = \left( \sum_{i=1}^{N_x} x_i w_{ki} \right) + \theta_k, \qquad k=1,2,\ldots,N_z \qquad (1)$$

Where $N_z$ is the number of neurons in the hidden layer, $w_{ki}$ is the weighting factor and $\theta_k$ is the bias term. Let the activation function of the hidden layer be the sigmoid function $f(\zeta)$, where

$$f(\zeta) = \frac{1}{1+e^{-\zeta}} \qquad (2)$$

then the output from the $k_{th}$ neuron of the hidden layer is $z_k$ as in Eq.3.

$$z_k = f(\gamma_k) \qquad (3)$$

the output of the $j_{th}$ neuron in the output layer is,

$$y_j = \left( \sum_{k=1}^{N_z} z_k w_{jk} \right) + \eta_j, \qquad j=1,2,\ldots,N_y \qquad (4)$$

with $w_{jk}$ being the weighting factor and $\eta_j$ the bias term.

The training process is in fact an optimization problem to find the best values for $w_{ki}, \theta_k, w_{jk}, \eta_j$ to minimize the objective function, which is square of the difference between the output from the ANN and the training data.

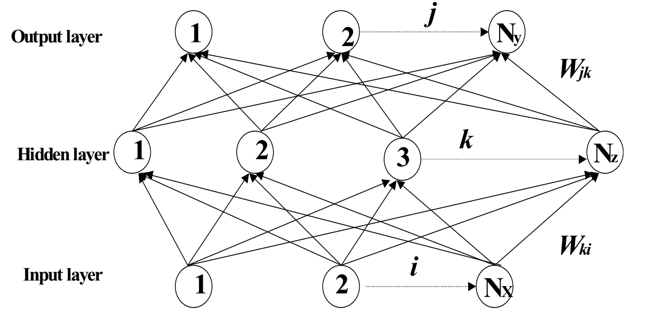


Fig. 3. The used 3-layer MLP structure.

## IV. NONLINEAR MODEL

The nonlinear model equivalent of the intrinsic small–signal circuit is shown in Fig. 4. We model the non-linear DC currents $I_B$ and $I_C$ as a function of $V_{B'E}$ and $V_{C'E}$ i.e.

$$I_B = I_{B'E} = f_B(V_{B'E}, V_{C'E}) \qquad (5)$$

$$I_C = I_{C'E} = f_C(V_{B'E}, V_{C'E}) \qquad (6)$$

We construct the two functions $f_B$ and $f_C$ with an ANN of the MLP-3 type. For that purpose, we collect 350 sample measured DC data. The range of measurements takes into account non-ideal currents (low base voltage region) and Kirk effect (high base voltage region). We bias our device with $V_B$ ranging from 0.6 V to 1.2 V, for $V_C$ from 0 voltage to 2 V, and measure the terminal currents $I_B$ and $I_C$. We subdivide our set of data into two sets: 250 sample data are used for training, while the other 100 are used to test the ANN. Our neural network consists of 3 layers: an input layer (2 inputs) for $V_{BE}$ and $V_{CE}$, a hidden layer (8 neurons), and an output layer (2 outputs) for $I_B$ and $I_C$. The test error is less than 1%.

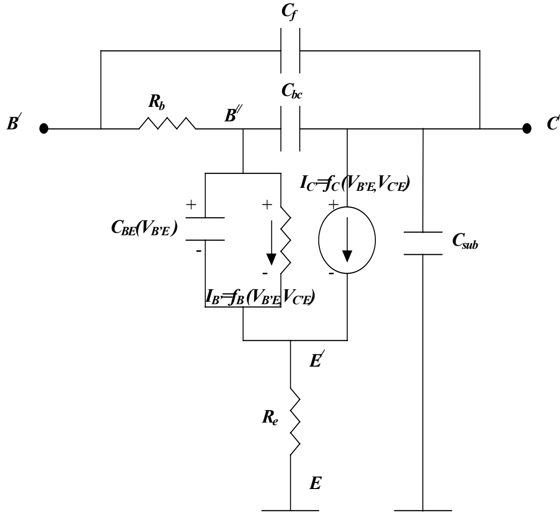


Fig. 4. Intrinsic non-linear model

The non-linear capacitance is modeled using [7], which assumes linear extrapolation in forward bias:

$$C_{B'E}(V_{B'E}) = \begin{cases} \dfrac{C_{BE0}}{(1-\dfrac{V_{B'E}}{V_O})^{m_{jo}}} \text{.................................} V_{B'E} < \dfrac{V_O}{2} \\ 2^{mjo} C_{BEO}\left[2m_{jo}\dfrac{V_{B'E}}{V_O} + 1 - m_{jo}\right] \text{............} V_{B'E} \geq \dfrac{V_O}{2} \end{cases} \quad (7)$$

with $C_{BEO}$ the value of the emitter-base junction capacitance at $V_{BE}$=0 V, $V_O$ the emitter-base barrier potential, and $m_{jo}$ the emitter-base capacitance gradient factor. These three parameters are extracted by varying iteratively them up to get the best non-linear matching.

## V. Model Verification

The nonlinear model for a 0.8 µm x 9.6 µm Si/SiGe HBT was extracted and implemented in ADS. To validate the model, we first compare the DC measured and modeled currents. Fig. 5 shows $I_C$ where an excellent agreement is noticed. The same excellent agreement for $I_B$ is shown in Fig. 6. For large-signal validation, we compare measured and simulated output harmonics in Fig. 7. The device is biased at $V_{BE}$=0.9 V, $V_{CE}$=1.5 V, the fundamental frequency $f_o$ equals 5.5 GHz and the power is varied between –40 dBm to –10 dBm. The model predicts well the measured fundamental and harmonics, Fig. 7 shows this fact. Using LSNA measurement setup, a time domain comparison is made for $i_c$ in Fig. 8 and $i_b$ in Fig. 9 at an input power of –10 dBm.

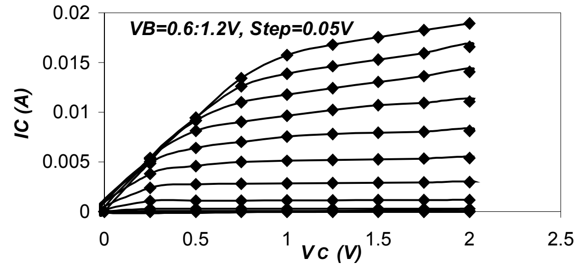


Fig. 5.a. Measured $I_C$ as function of $V_B$ and $V_C$

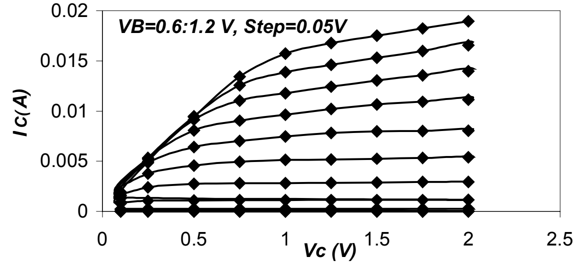


Fig. 5.b. Modeled $I_C$ as function of $V_B$ and $V_C$

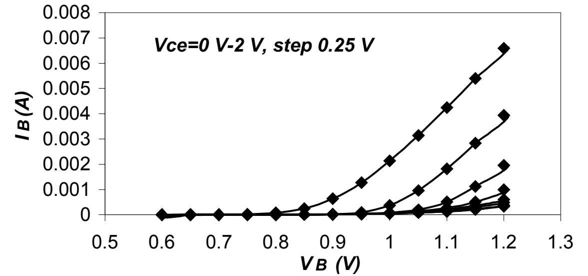


Fig. 6.a.. Measured $I_B$ as function of $V_B$ and $V_C$.

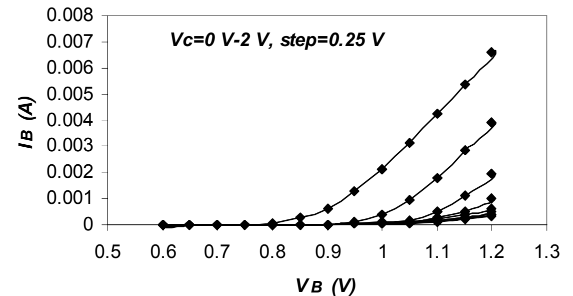


Fig. 6.b. Modeled $I_B$ as function of $V_B$ and $V_C$

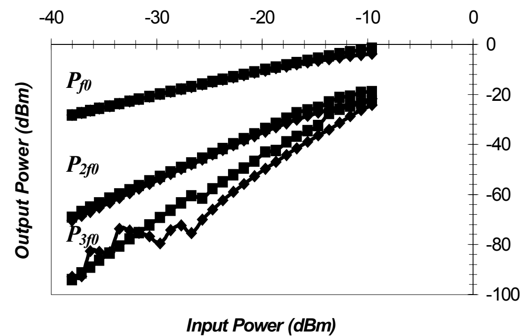


Fig. 7. Comparison between measured (■) and modeled (▲) fundamental, second, and third harmonics

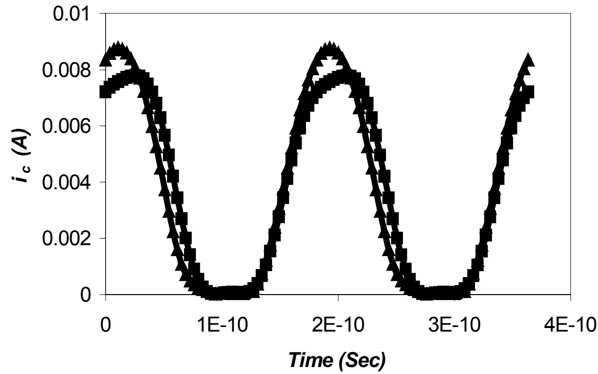


Fig. 8. Comparison between de-embedded measured (■), and modeled (▲) $i_c$ $f_o$=5.5 GHz,$P_{in}$=-10 dBm.

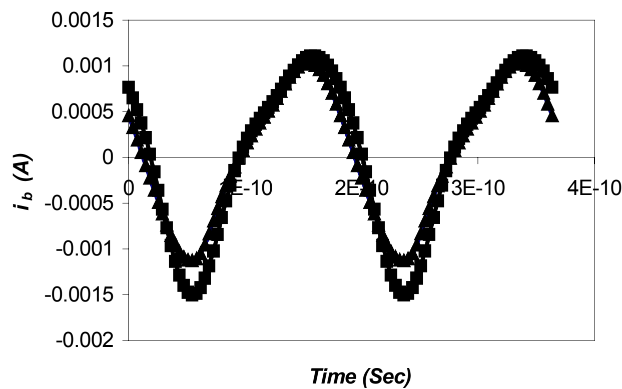


Fig. 9. Comparison between de-embedded measured (■), and modeled (▲) $i_b$ $f_o$=5.5 GHz,$P_{in}$=-10 dBm.

## VI. Conclusion

We developed a new ANN-based nonlinear model for Si/SiGe HBT. In comparison to compact models, ANN is simple to extract. Moreover, we can include all non-linear effects via the ANN model. DC and large-signal measurements have validated the model.

## Acknowledgement

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