Extraction of Small Signal Equivalent Circuit Model Parameters for Statistical Modeling of HBT Using Artificial Neural

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***Abstract*—We found different performances for the same device due to the variations in the process from die to the other on the same wafer or on another one. Yield analysis becomes one of the important tools into commercial Computer Aided Design (CAD) programs. Statistical issues are crucial in yield analysis for microwave circuits. Yield analysis needs accurate statistical properties between the parameters of devices' models to reflect correctly the physical variations. Normally, on the level of the device modeling, the statistical properties between the model parameters like means and standard deviations are noisy by using the known techniques (optimization-based and direct) for extracting the small signal equivalent circuit model parameters of active microwave devices. We introduce how is Artificial Neural Network (*ANN*) accurate and efficient statistical extraction method for small signal model parameters of Hetero Junction Bipolar Transistor (HBT). Utilizing this methodology provides a robust statistical model for our device.**

I. Introduction

Both of the optimization based extraction and direct extraction techniques provide the statistical model with noise in terms of uncertainty coming from stop criterion for the former technique and measurements accuracy of selected data points used in the later one [1]. To overcome this problem, authors suggested building inverse function to extract the model parameters from the model performances (measured quantities). This technique gives a unique solution and controls the noise and is called Recursive Inverse Approximation (RIA). Firstly, the nominal device (device which has a performance close to the average performance) is extracted using a global optimization technique. RIA assumes that the changes between the model parameters for the devices are very small, and therefore it approximates the function of the model parameters of any device by Taylor series expansion around the extracted parameters vector of the nominal device. Then some estimated parameters obtained by sampling around the vicinity of the nominal parameters (model parameters for the nominal device) used in accuracy checking and parameter corrections. They applied it to SPICE level 3 model parameters for MOSFET. In this paper, we construct this map or function by using Artificial Neural Network (*ANN*). *ANN* learns the required relation between model parameters domain and performance (measured or simulated quantities) domain from these estimated parameters and their corresponding performances (training data). We apply this methodology to extract small signal equivalent circuit model parameters for Hetrojunction Bipolar Transistor (HBT). This paper is organized as follows: the statement of the problem is in section II, we show the theory of the used ANN technique in section III, implementation and results are shown in section IV, and finally the conclusion is drawn in section V.

II. Problem Identification

The complete equivalent scheme of an HBT as seen from the probe tips is shown in Fig. 1. It can be subdivided into two parts: the intrinsic core of the device (bias-dependent), and the external pad parasitics (which are bias-independent). In [2], the sensitivity analysis proves that the S-parameters are insensitive with respect to parasitic parameters, and also with respect to C_{be} and R_{be}. So our interest is focused only to obtain values of the rest of the intrinsic part shown in Fig.2, namely C_{bc}, C_f, G_m, R_b and R_e for each device. The insensitive parameters of all devices will be the same as for nominal device. The relationship between the 5 remaining model parameters and the measured S-parameters is represented by an ANN model.

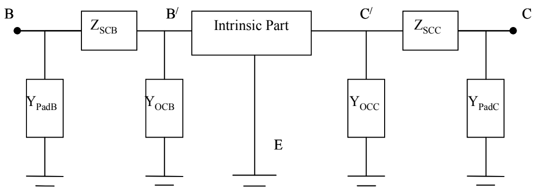

Fig. 1 Representation of the SiGe HBT in the measurement configuration. The actual transistor is represented by the rectangle called 'intrinsic transistor'. The series impedances and parallel admittances model the probe pads and access transmission lines.

A big challenge concerned the selection of an optimal set of input variables. The most straightforward approach would be to consider the four S-parameters at all measured frequency points, but this quickly counts up to a huge number of input parameters. As alternative approach, we propose to take the 8 complex mean of the real and imaginary parts of the S-parameters over the considered frequency range as inputs for the ANN. As example the first and second inputs of our neural network become

$$Input(1) = \frac{1}{N}\sum_{i=1}^{N}\mathrm{Re}(S_{11})_i \tag{1}$$

$$Input(2) = \frac{1}{N}\sum_{i=1}^{N}\mathrm{Im}(S_{11})_i \tag{2}$$

Where: Re $(S_{11})_i$ and Im $(S_{11})_i$ are the real and Imaginary parts of (S_{11}) at frequency point 'i' and 'N' is the total number of all frequency point

Let the performance vector for our case to be S.

$$S = [mean(\mathrm{Re}(S_{11})) \quad mean(\mathrm{Im}(S_{11})) \quad \ldots \quad mean(\mathrm{Im}(S_{22}))]^T \tag{3}$$

Let also the most sensitive equivalent circuit model parameters be

$$X = [C_f \quad C_{bc} \quad G_m \quad R_b \quad R_{ei}]^T \tag{4}$$

We want to find a map such that $S \in \Re^8 \rightarrow X \in \Re^n$, where m is the number of measured frequency points, and n is the number of most sensitive model parameters. The requirement is to construct ψ such that,

$$X = \psi(S) \tag{5}$$

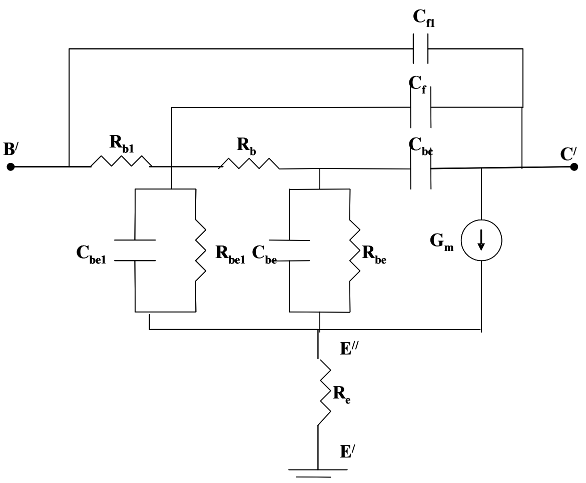

Fig. 2 Intrinsic part of the device

III. Artificial Neural Network

The ANN is constructed through learning from a set of input/output data (training set). 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 γ_k, calculated from the input variables by:

$$\gamma_k = \left(\sum_{i=1}^{N_x} x_i w_{ki}\right) + \theta_k, \qquad k=1,2,\ldots,N_z \tag{6}$$

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

$$f(\zeta) = \frac{1}{1+e^{-\zeta}} \tag{7}$$

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

$$z_k = f(\gamma_k) \tag{8}$$

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

$$y_j = \left(\sum_{k=1}^{N_z} z_k w_{jk}\right) + \eta_j, \qquad j=1,2,\ldots,N_y \tag{9}$$

with w_{jk} being the weighting factor and η_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.

IV. Implementation and Results

To validate our methodology, we carried out a controlled experiment i.e we know both of most sensitive small signal equivalent circuit model parameters and the corresponding performances beforehand (test data) for each device. Firstly, we determine the nominal device, by characterizing 23 devices from different wafers with a geometry of 0.8 µm x 9.6 µm on a *Si/SiGe* HBT in the frequency range from 1 GHz to 20GHz, biased at V_{BE} =0.9 V and V_{CE} =1.5V and taking the device which has average performance over all the measured devices as a nominal device. Secondly, we extract the small signal equivalent circuit model parameter values for the nominal device using [2], again these model parameters are called the nominal parameters. Thirdly, we use small signal equivalent circuit model shown in Fig. 2 to generate twenty data using Monte Carlo simulations utility in *ADS* (Advanced Design System), they are used as test data. We vary the model parameters [X] according to known statistics (means, slandered deviations and correlations) to get the corresponding performance [S]. These data represent the performance of 20 devices. Similarly, another one hundred Monte Carlo simulations was performed randomly around the vicinity (±10%, the maximum limit the model parameter can deviate from the nominal value) of the nominal parameters to get the corresponding performances and together they constitute the training data, we use these samples to train the ANN using the back-propagation algorithm [3], as implemented in the Neuro-Modeler program [4]. To prove the effectiveness of ANN to obtain better statistically model more than the conventional extraction methods, we extract the model parameters also with optimization based extraction [2] for the same *S* used in test data. The comparison between the extracted model parameters from ANN, extracted with optimization-based method and the original test data is shown in Figs.3-7 for C_{bc},C_f, G_m, R_b *and* R_e respectively. From the comparisons we can say that ANN is more accurate in extracting our model parameters than if we extract those parameters using conventional extraction methods. To statistically validate our extraction methodology, we compare the means and standard deviations of the test data and the extracted data with the two methodologies in Table I, also the correlations between test data and corresponding correlations as extracted from *ANN* model and optimization-base [2] are compared in Tables II-IV.

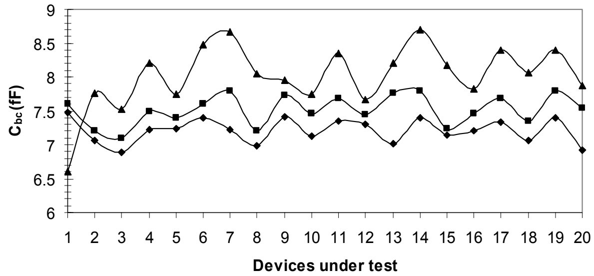

Fig. 3. Comparison between Tested data (■), extracted with optimization-based (▲) and the extracted with *ANN* (♦) for C_{bc} parameter

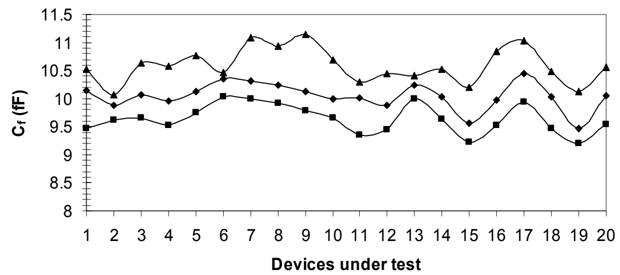

Fig. 4 Comparison between Tested data (■), extracted with optimization-based (▲) and the extracted with *ANN* (♦) for C_f parameter

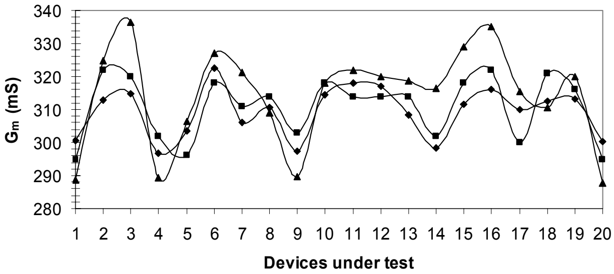

Fig.5 Comparison between Tested data (■), extracted with optimization-based (▲) and the extracted with *ANN* (♦) for G_m parameter

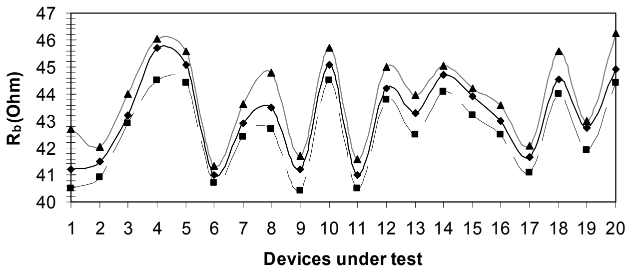

Fig.6 Comparison between Tested data (■), extracted with optimization-based (▲) and the extracted with *ANN* (♦) for R_b parameter

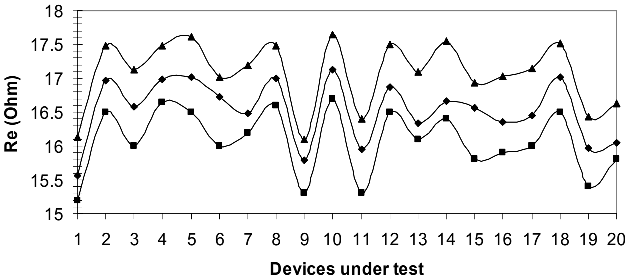

Fig. 7 Comparison between Tested data (■), extracted with optimization-based (▲) and the extracted with *ANN* (♦) for R_e parameter

Most sensitive equivalent circuit model parameters	Mean			Standard Deviation		
	ANN	Tested data	Optimization based	*ANN*	Tested data	Optimization based
G_m	309.29	311	314.28	11.57	9.30	15.12
R_b	43.21	42.6	43.89	1.59	1.46	1.59
R_e	16.52	16.1	17.07	0.46	0.47	0.49
C_{bc}	7.51	7.21	8.01	0.21	0.17	0.47
C_f	10.04	9.64	10.59	0.23	0.25	0.31

TABLE I

COMPARISON BETWEEN MEANS AND STANDARD DEVIATIONS FOR TEST DATA, *ANN*-BASED METHODOLOGY AND OPTIMIZATION-BASED TECHNIQUE

	C_{bc}	C_f	G_m	R_b	R_e
C_{bc}	1				
C_f	-0.10	1			
G_m	-0.33	-0.09	1		
R_b	-0.45	-0.13	-0.12	1	
R_e	-0.47	0.29	0.26	0.74	1

TABLE II

CORRELATION BETWEEN THE MODEL PARAMETERS OF TESTED SAMPLES

	C_{bc}	C_f	G_m	R_b	R_e
C_{bc}	1				
C_f	-0.24	1			
G_m	-0.30	-0.11	1		
R_b	-0.34	-0.24	-0.29	1	
R_e	-0.54	0.40	0.24	0.56	1

TABLE III

CORRELATION BETWEEN THE EXTRACTED MODEL PARAMETERS WITH *ANN*

	C_{bc}	C_f	G_m	R_b	R_e
C_{bc}	1				
C_f	0.04	1			
G_m	-0.28	-0.24	1		
R_b	-0.07	0.03	-0.26	1	
R_e	-0.20	0.03	0.29	0.56	1

TABLE IV

CORRELATION BETWEEN THE EXTRACTED MODEL PARAMETERS WITH OPTIMIZATION-BASED TECHNIQUE

V. CONCLUSION

In this paper we used *ANN* as learning tool to construct map between the average of *S*-parameters over the whole frequency range and the most sensitive small signal model parameters. We also showed that *ANN* model preserves the statistical relations between the extracted model parameters.

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