A COMPARISON BETWEEN HBT SMALL-SIGNAL MODEL OPTIMIZATION USING A GENETIC ALGORITHM AND DIRECT PARAMETER EXTRACTION

M. Borgarino, R. Menozzi, J. Tasselli°, and A. Marty°

Dipartimento di Ingegneria dell'Informazione, University of Parma
Viale delle Scienze, 43100 Parma, Italy
Tel. +39-521-905832 / Fax +39-521-905822 / e-mail r_menozzi@ee.unipr.it
° Laboratoire d'Analyse et d'Architecture des Systemes – CNRS, Toulouse, France
Tel. +33-561-336435 / Fax +33-561-336208 / e-mail marty@laas.fr

ABSTRACT

This work for the first time shows that physically meaningful, wideband, multi-bias small-signal modeling of HBTs can be efficiently and accurately achieved using a Genetic Algorithm (GA). The physical significance of the equivalent circuit parameters extracted by the GA was checked using a Direct Extraction Technique (DET). The two procedures were applied to HBT S-parameters measured at different bias points. The simulated S-parameters match very well with the measured ones over the whole frequency range investigated. For each point we obtained quite a good agreement between the parameters extracted by the DET and by the GA, which demonstrates the ability of the GA to efficiently extract a physically significant HBT small-signal model.

INTRODUCTION

The small-signal modeling of microwave transistors is typically accomplished in either of two fundamental ways, namely, numerical optimization or direct parameter extraction. Among the weaknesses of the former are the tendency of gradient-based optimization techniques to get stuck in local minima of the error function, and the need to independently check the physical meaning of the extracted parameters. On the other hand, direct extraction techniques are cumbersome and more sensitive to measurement errors but, within specific limitations on the frequency range and bias conditions, may provide physically significant values for the equivalent circuit parameters.

A small-signal model (SSM) optimization technique based on a Genetic Algorithm (GA) was recently presented and applied to MESFETs, HEMTs, and HBTs (1-3). This method, that mimics the natural mechanisms driving the evolution of species, was demonstrated to be an efficient optimizer for complex equivalent circuits (up to 19 parameters) and to be able to overcome the local minima problem of gradient-based techniques, even with hardly any *a priori* knowledge of the values of the equivalent circuit parameters.

This work for the first time tackles the issues connected with the physical meaning of the HBT small-signal model optimized by the GA, by comparing the GA-optimized SSM parameters with those extracted using a direct extraction technique that does not rely on numerical optimization.

THE GENETIC ALGORITHM

In this section we give a short description of the GA devised for HEMT and HBT SSM optimization. More details can be found elsewhere (1); a very good general reference on GAs is the book of D. E. Goldberg (4).

Genetic Algorithms are stochastic optimizers that imitate the evolution of natural species toward generations with ever better average *fitness*. Here the fitness of an *individual,* i.e., of a particular set of SSM parameters (representing a possible solution to the optimization problem) is defined as C - ε, where ε is the error norm (1^{st} and 2^{nd} order norms are typically used in SSM optimization; in particular, a 1^{st} order norm was used throughout this work) that measures the difference between experimental and modelled S-parameters, and C is a constant chosen so that the fitness be always positive and suitably scaled.

One of the main advantages of GAs is that they work in parallel on a large number *n* (typically $n > 50$) of individuals, called the *population* $\mathcal{P}$, thus simultaneously exploring several points of the search space. Starting from an initial $\mathcal{P}$ (chosen randomly within bounds specified by the user at run time), the GA produces successive populations with increasing average fitness, i.e., SSMs that match with the measured data better and better. The random choice of the initial $\mathcal{P}$ implies that the problems connected with the choice of the initial solution (a well-known issue for gradient-based optimizers) disappear altogether. The user only needs to define a lower (π_i^{min}) and upper (π_i^{max}) bound for each SSM parameter (π_i). These bounds may be extremely loose, e.g., $\pi_i^{max} / \pi_i^{min} = 10^2 \div 10^4$, without compromising the final result.

Each individual is coded as a bit string obtained by suitably joining the binary-coded values of the parameters π_i.

Three main mechanisms drive the GA toward generations with increasing fitness:

1. *Reproduction*, that creates a new offspring by copying the *n* individuals of $\mathcal{P}$ into a transient population $\mathcal{P}_t$ (also made up of *n* individuals) with a probability that increases with their fitness ("survival of the fittest"). This implies that $\mathcal{P}_t$ tends to have a better average fitness than $\mathcal{P}$.
2. *Crossover*, an exchange of string fragments between randomly paired individuals of $\mathcal{P}_t$ (the *parents*). This operator is applied with a probability p_c, and simulates the exchange of parent genes taking place when an offspring is born. The goal is to generate new solutions to the optimization problem than may turn out to be fitter than the parent solutions.
3. *Mutation*, making a 0 become 1 and viceversa, an operator that is randomly applied bit-by-bit to the individuals of $\mathcal{P}_t$, with a probability p_m. Mutation helps exploring randomly chosen regions of the search space, thus avoiding that the GA get stuck in local minima.

After crossover and mutation, the individuals of $\mathcal{P}_t$ are evaluated, i.e., the error ε and the fitness are calculated for each one of them. Then, $\eta \times n$ ($0 \le \eta \le 1$) randomly chosen individuals of $\mathcal{P}$ are included into $\mathcal{P}_t$ (*Partially Elitistic procedure*, a distinctive feature of our GA), and the new population $\mathcal{P}$ is formed by picking the *n* fittest individuals of $\mathcal{P}_t$. The Partially Elitistic procedure helps avoiding that good individuals be lost as the population evolves (for $\eta = 1$ we get a fully elitistic GA, which guarantees that no individual can be substitued, in the following generation, by one with a lower fitness), and turns out to make the algorithm more flexible and efficient.

Finally, a semi-heuristic local search procedure can be performed in the surroundings of the best individual(s), in order to further increase the best fitness of $\mathcal{P}$.

The GA iterates the cycle described so far (corresponding to a *generation*) until it reaches *genetic saturation*, i.e., until the fitness of the best individual and the average fitness of $\mathcal{P}$ differ by less than a predefined threshold (ε_{sat}).

The GA sketched above was implemented in C++ for Windows and applied to the small-signal modelling of GaAs MESFETs, GaAs PHEMTs, InP HEMTs and GaAs HBTs over wide ranges of frequency. The computation time for a run of the GA (from the creation of the initial $\mathcal{P}$ to saturation) depends on a number of factors, including the number of individuals of $\mathcal{P}$ and the number of frequency points of the S-parameter data set, but typically ranges from 2-10 min on a Pentium 120 PC (for n in the range of 100 and 40 frequency points). It is worth noticing that the stochastic nature of GAs implies that, in general, each run outputs a different result. Nevertheless, a well-tailored GA will yield results that do not differ too much from run to run, so that a very limited number of runs is typically needed to achieve a satisfactory solution to the optimization problem.

HBT MODEL OPTIMIZATION AND PARAMETER EXTRACTION

In order to check the significance of the equivalent circuit parameters provided by the GA, we applied a direct extraction technique (DET) that we developed starting from the works of Pehlke and Pavlidis, Laser and Pulfrey, and Dambrine et al. (5-8). Both the GA and the DET use the classical π-model of the intrinsic device, with R-L parasitics connected in series with each electrode (Fig. 1). Since any physical description of the device must include an intrinsic subcircuit, whose elements are bias-dependent, and an outer shell of bias-independent parasitics, a significant benchmark for the model's physical soundness must include different bias points.

Following the approach used by Dambrine et al. (8) for FETs, the DET first determines the extrinsic parameters, that are then de-embedded in order to allow the extraction of the intrinsic parameters. As Pehlke and Pavlidis do (5), we neglect the pad capacitances. For the extraction of the emitter and base parasitics, we used an impedance representation of the device, as suggested by Spiegel et al. (9). In particular, we obtained the following expressions:

$$d\mathrm{Im}\{Z_{12}\}/d\omega = L_E - C_{BE}[(1/R_{BE} + g_m)^2 - \omega^2 C_{BE}^2] / [(1/R_{BE} + g_m)^2 + \omega^2 C_{BE}^2]^2 \quad (1)$$

$$\mathrm{Re}\{Z_{12}\} = R_E + (1/R_{BE} + g_m) / [(1/R_{BE} + g_m)^2 + \omega^2 C_{BE}^2] \quad (2)$$

$$\mathrm{Re}\{Z_{11}\} - \mathrm{Re}\{Z_{12}\} = R_B \quad (3)$$

$$\mathrm{Im}\{Z_{11}\} - \mathrm{Im}\{Z_{12}\} = \omega L_B \quad (4)$$

from which we extract L_E, R_E, R_B and L_B, respectively. Due to the low values of the emitter inductances (confirmed by the GA optimization), the first equation only allows to find an upper bound for L_E. For the extraction of the collector parasitics, we use the method proposed by Pehlke and Pavlidis (5), because it gives more handy formulas. In the technique of ref. (5), however, the extraction of L_C is possible only after obtaining the value of C_{BC}, which is an intrinsic parameter. This procedure is not compatible with Dambrine's approach, that requires the determination of the extrinsic parameters as a first step. We therefore modified the technique of (5), in order to obtain a procedure compatible with Dambrine's. While the method of (5) uses only data taken in the forward active region (FAR), in our work the extraction of L_C is performed by biasing the device in the reverse active region (RAR). In the RAR, the base-collector junction is forward-biased, hence it presents a much lower differential resistance. If we look at the expression used in (5) to extract L_C, we notice that this condition is favourable for the determination of L_C, since it allows to skip the extraction of C_{BC}. It is worth pointing out that, instead, the FAR is the most useful condition for the extraction of R_C, because of the high value of the base-collector resistance.

The parasitics thus obtained are then de-embedded using a Y-matrix rappresentation of the HBT, in the same way as proposed in (8). The intrinsic parameters are extracted from the Y-matrix rappresentation of the intrinsic device. From the expression of Y_{11} and Y_{12} we obtain C_{BC} and C_{BE}:

$$\mathrm{Im}\{Y_{12}\} = -\omega C_{BC} \quad (5)$$

$$\mathrm{Im}\{Y_{11}\} + \mathrm{Im}\{Y_{12}\} = \omega C_{BE} \tag{6}$$

The base-emitter resistance is directly obtained as:

$$R_{BE} = (\mathrm{Re}\{Z_{12}\}_{\omega\to 0} - R_E) / (1 - \alpha_0) \tag{7}$$

The transconductance was obtained, following Laser and Pulfrey (7), from the DC common-base current gain α_0 (simply measured as $I_C/(I_B+I_C)$, as suggested by Samelis and Pavlidis (6)). With respect to the equation in (7), we neglected the effect of the collector-base depletion region transit time, which for our devices was estimated to be very small in the frequency range we consider.
Since at this point all the parameters are known, with the sole exception of the delay τ, we extracted this last parameter by minimizing the error between the measured and simulated S_{21}, using τ as a fitting parameter.
In Fig. 2 we show measured and modeled (both using the GA and the DET) S-parameters of a 10x200 μm^2 AlGaAs/GaAs HBT featuring β= 50 and cutoff frequencies f_T and f_{MAX} of 20 GHz and 13 GHz, respectively. The very good match between the measurements and the models proves that both modeling approaches are able to correctly describe the wideband small-signal behavior of the HBTs under different bias conditions.
As far as the equivalent circuit parameters are concerned, in Table I we show, for 4 different bias conditions, those extracted using both the DET and the GA. We found an overall good agreement between the two sets. The only two relevant exceptions, namely, R_{BE} and τ, can be easily explained if we consider that: (i) in the whole frequency range we used (0.55-20.05 GHz), R_{BE} is shunted by a much smaller $1/\omega C_{BE}$; (ii) even at the upper end of the frequency range, a τ in the range of 0.2 ps (as obtained by the DET) introduces a phase delay of only about 0.025 rad. These two circumstances make it very hard for the GA to extract precise values for R_{BE} and τ.
It should be noticed that the parasitic elements turned out to be, as they must, practically bias-independent, which is an important indicator of the physical soundness of the HBT model.
It is also very important to point out that the GA was able to converge to a physically meaningful solution even though, in order to test the algorithm under worst-case conditions, the equivalent circuit parameter values were allowed to span over 4 orders of magnitude during the optimization process.

CONCLUSIONS

In this work we have shown that physically meaningful, wideband, multi-bias small-signal modeling of HBTs can be efficiently and accurately achieved using a Genetic Algorithm. The physical significance of the equivalent circuit parameters extracted by the GA was checked using a Direct Extraction Technique. The two procedures were applied to AlGaAs/GaAs HBT S-parameters measured at different bias points in the 0.55-20.05 GHz frequency range. The simulated S-parameters match very well with the measured ones over the whole frequency range investigated. For each point we obtained quite a good agreement between the parameters extracted by the DET and by the GA (with some intrinsic limitations on the base-emitter resistance and the transconductance delay), which demonstrates the ability of the GA to efficiently extract a physically significant HBT small-signal model, even under quite unfavorable conditions from the standpoint of the *a priori* knowledge of the model parameters (which were allowed to span over 4 orders of magnitude in our GA runs).

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	DET / GA I_B= 18 μA V_{CE}= 2 V	DET / GA I_B= 18 μA V_{CE}= 4 V	DET / GA I_B= 100 μA V_{CE}= 4 V	DET / GA I_B= 100 μA V_{CE}= 2 V
R_B (Ω)	2.07 / 1.38	2.04 / 2.08	2.16 / 2.07	2.07 / 2.08
L_B (pH)	77.3 / 100	77.3 / 81.4	77.3 / 81.7	77.3 / 81.4
R_E (Ω)	1.88 / 1.87	1.86 / 1.75	2.20 / 1.99	2.24 / 2.02
L_E (pH)	< 7 / 0.003	< 7 / 0.001	< 7 / 0.004	<7 / 0.008
R_C (Ω)	0.57 / 0.33	0.56 / 0.23	0.48 / 0.14	0.52 / 0.36
L_C (pH)	68.9 / 64.9	68.9 / 65.0	68.9 / 64.5	68.9 / 63.6
R_{BE} (Ω)	1270 / 443	1300 / 765	205 / 174	220 / 198
C_{BE} (pF)	7.70 / 7.83	7.48 / 8.00	11.6 / 12.3	10.1 / 11.7
C_{BC} (pF)	2.43 / 2.54	1.72 / 1.87	1.71 / 1.75	2.08 / 2.40
g_m (mS)	29.5 / 26.4	30.0 / 27.5	239 / 236	223 / 240
τ (ps)	0.22 / 0.86	0.24 / 1.71	0.18 / 2.47	0.13 / 0.65

Table I : Comparison between the HBT small-signal model parameters extracted by the DET and by the GA.

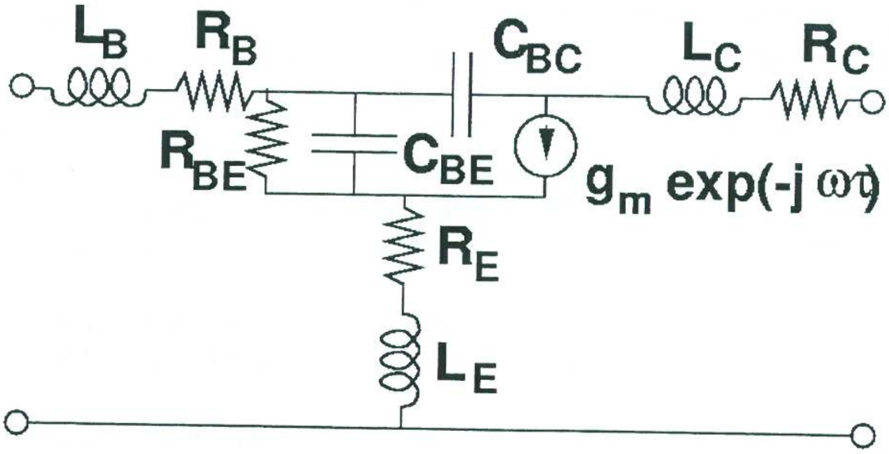

Fig. 1 : HBT small-signal model used by both the GA and the DET.

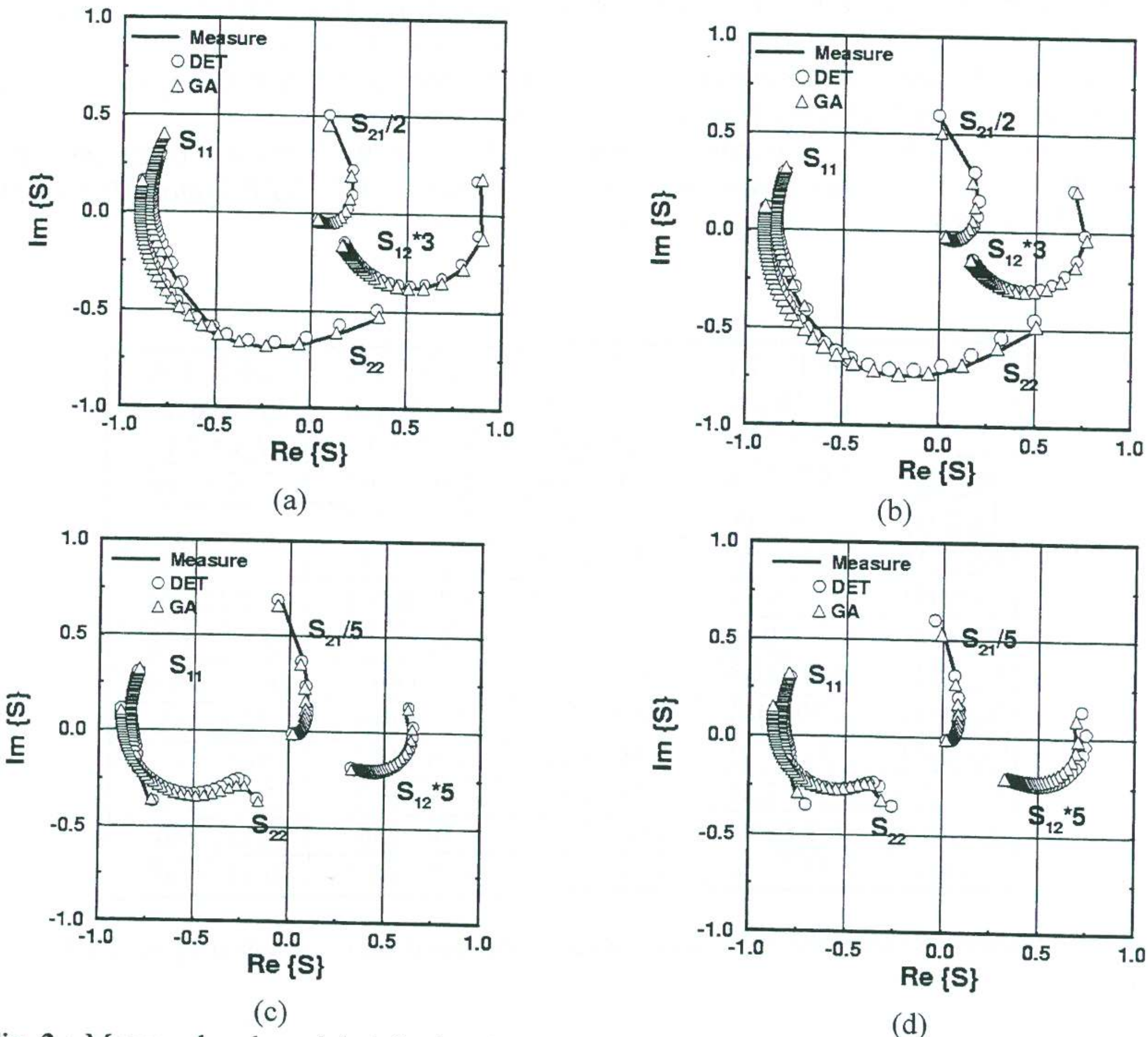

Fig. 2 : Measured and modeled (both using the GA and the DET) S-parameters of one of the HBTs under test, between 0.55 and 20.05 GHz, under different bias conditions: (a) I_B= 18 μA, V_{CE}= 2 V; (b) I_B= 18 μA, V_{CE}= 4 V; (c) I_B= 100 μA, V_{CE}= 4 V; (d) I_B= 100 μA, V_{CE}= 2 V.