Robust Framework for Efficient RF/Microwave System Modeling Using Neural- and Fuzzy-Based CAD Tools

Z. CHENG *, L. JI *, S. GAOUA **, F.A. MOHAMMADI ***, M.C.E. YAGOUB *

* SITE, University of Ottawa,
Ottawa, Ontario, K1N 6N5
CANADA

** Faculty of Electronics and Informatics, USTHB,
B.P. 32, Bab-Ezzouar, Algiers, 16111
ALGERIA

*** ECE Department, Ryerson University,
Toronto, Ontario, M5B 2K3
CANADA

Abstract: - The design of RF/microwave systems requires fast and accurate modeling tools. This aspect is crucial when the design process leads to massive and highly repetitive computational tasks during simulation, optimization and statistical analysis. In this paper, we present a robust framework that combines the capabilities of neural networks and fuzzy systems to automatically predict, at the component level, the most reliable equivalent circuit model of most widely used RF/microwave transistors, i.e., MESFETs and HBTs. Thus, the proposed approach is demonstrated, at the circuit level, through CAD of an amplifier circuit.

Key-Words: - Circuit CAD, Transistor Modeling, Fuzzy Neural Networks, PKI Neural Networks.

1 Introduction

In this information age, the rapid growth of today's RF/microwave communication systems requires a continuous upgrading of existing computer-aided design tools. Furthermore, the needs for concurrent and multi-disciplinary design with simultaneous consideration of electrical and reliability criteria become increasingly important. This trend leads to massive and highly repetitive computational tasks during simulation, optimization and statistical analyses, requiring that the component models be not only fast but also accurate so that the design can be achieved accurately and reliably. Therefore, the efficiency of such Computer Aided Design (CAD) tools relies heavily upon the speed and accuracy of their most sensitive device models, particularly the active components such as Metal-Semiconductor Field Effect Transistors (FETs) and Heterojunction Bipolar Transistors (HBTs) [1].

Since FETs and HBTs are widely used in the RF/microwave area, a large number of modeling approaches are being proposed. Detailed physics-based transistor models are accurate but slow. Table look-up models can be fast, but suffer from the disadvantages of large memory requirements and limitations on number of parameters. Nevertheless they are difficult to develop, equivalent circuit models remain the most used modeling approach, where the element values can be determined either by direct extraction [1] or by optimization-based extraction [2]. Fast and simple to implement, direct-extraction techniques provide adequate values for the more dominant circuit model elements but they cannot determine all the extrinsic elements uniquely [3]. On the other side, optimization-based extraction techniques are more accurate but computationally intensive and sensitive to the choice of starting values. Though several optimization-based extraction methods that are insensitive to starting values have recently been proposed, it is still difficult to determine all the model elements with a high degree of certainty. Furthermore, in order to make them attractive to non-experienced users, such techniques often assume a *prior universal* transistor circuit topology referred in this paper as the *FET standard topology* or FET circuit # 1 (Fig. 1) [4] and the *HBT standard topology* or HBT circuit # 1 (Fig. 2) [5].

During the last decade, information processing techniques such as neural networks and fuzzy logic systems gained a particular attention as fast and reliable tools to RF/microwave device/circuit modeling and design. By combining the Fuzzy c-means method (FCM) and the small-signal neural representation of a device behavior, the proposed method allows efficient evaluation of the transistor small-signal equivalent circuit parameters [6] at the component level. Since the equivalent circuit is often specific to a given type of device and/or technology and it is puzzling to decide which one is most suitable for a given specific application, we created a library of the most often used equivalent circuit topologies, displayed in Fig. 3 to 6 [7]-[10] and in Fig. 7 to 10 [5], [11]-[13] for FETs and HBTs, respectively. Of course, this library is not exhaustive but contains most widely used models.

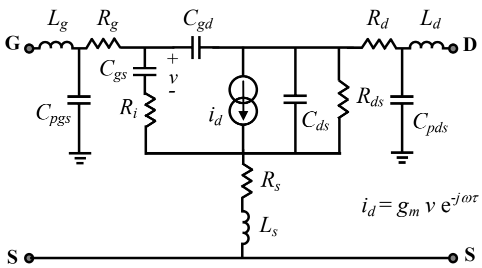

Fig. 1. FET standard topology (# 1).

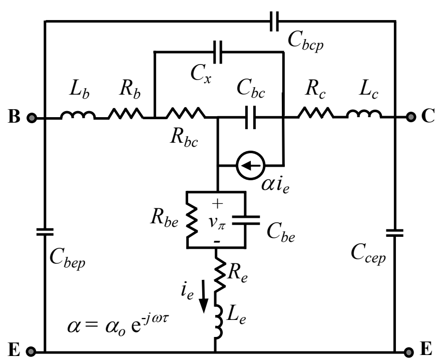

Fig. 2. HBT standard topology (# 1).

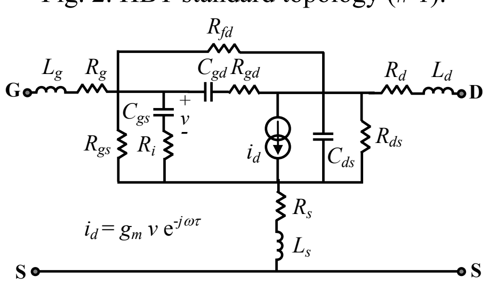

Fig. 3. FET circuit topology # 2 as reported in [7].

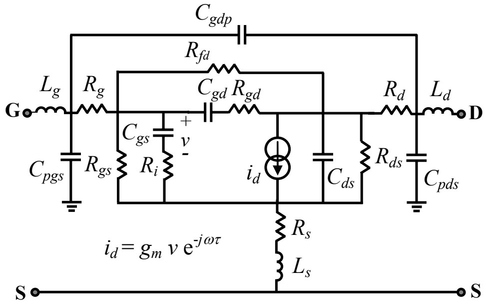

Fig. 4. FET circuit topology # 3 as reported in [8].

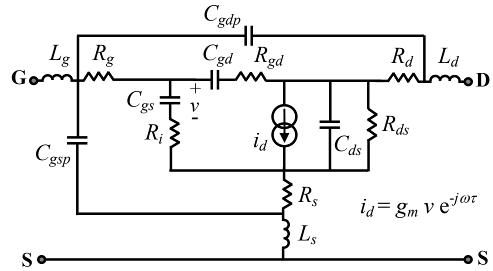

Fig. 5. FET circuit topology # 4 as reported in [9].

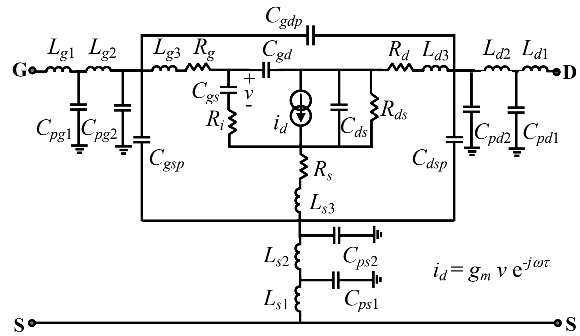

Fig. 6. FET circuit topology # 5 as reported in [10].

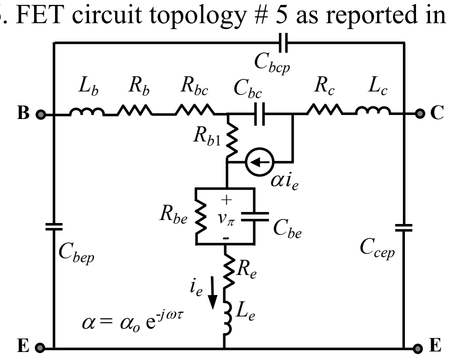

Fig. 7. HBT circuit topology # 2 as reported in [5].

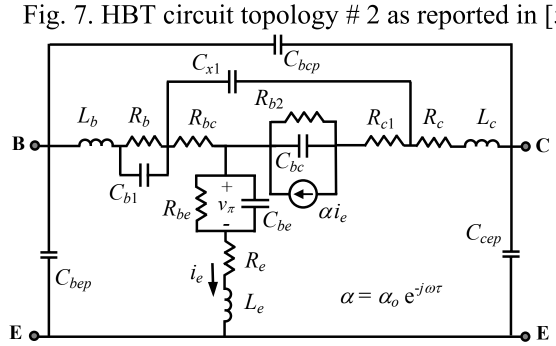

Fig. 8. HBT circuit topology # 3 as reported in [11].

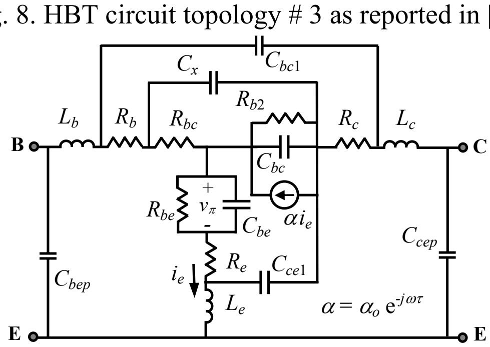

Fig. 9. HBT circuit topology # 4 as reported in [12].

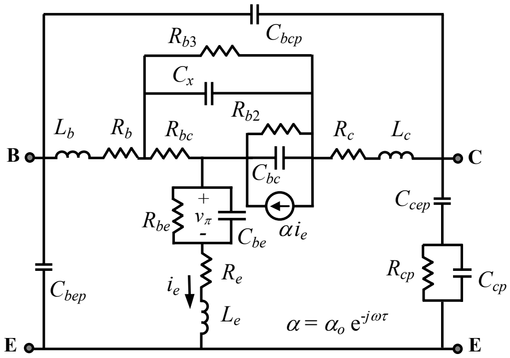

Fig. 10. HBT circuit topology # 5 as reported in [13]

Therefore, we developed a framework to include the circuit level modeling. For that purpose, a prior knowledge input (PKI) neural network was built to improve the training and prediction of the neural-based circuit model. The efficiency of the proposed device/circuit modeling unified framework is demonstrated through CAD of a three stage amplifier.

2 Device Level: Proposed Approach

The first step is a direct parameter extraction of the standard FET and HBT topology using the classical techniques described respectively in [1] and [5]. The obtained S-parameters ($S_{ij}^{\mathbf{s}}$, i, j = 1, 2) of the standard topology are then compared to the measured S-parameters (denoted as $S_{ij}^{\mathbf{m}}$, i, j = 1, 2), as shown in Fig. 11. If the achieved accuracy is not acceptable, a new circuit topology should be selected from the respective transistor library.

FCM is a data clustering technique wherein each data point belongs to a cluster to some degree that is specified by a membership grade. Clustering in N unlabeled data X = $\{x_i, i = 1,\ldots,N\}$ is the assignment of c number of partition labels to the vectors in X. The problem of clustering is to find the optimum matrix U = $[U_{ij} \in [0, 1], i = 1, ..., c; j = 1, ..., N]$ which minimize the function [14]

$$J_h(U,v) = \sum_{k=1}^{N}\sum_{i=1}^{c}(U_{ik})^h \left\|x_k - v_i\right\|^2 \tag{1}$$

where h is an exponent that controls the degree of fuzziness, u_{ik} describes the belongness of x_i to cluster k,

$$u_{ik} = \left(\sum_{j=1}^{c}\left[\frac{\left\|x_k - v_i\right\|}{\left\|x_k - v_j\right\|}\right]^{\frac{2}{h-1}}\right)^{-1} \tag{2}$$

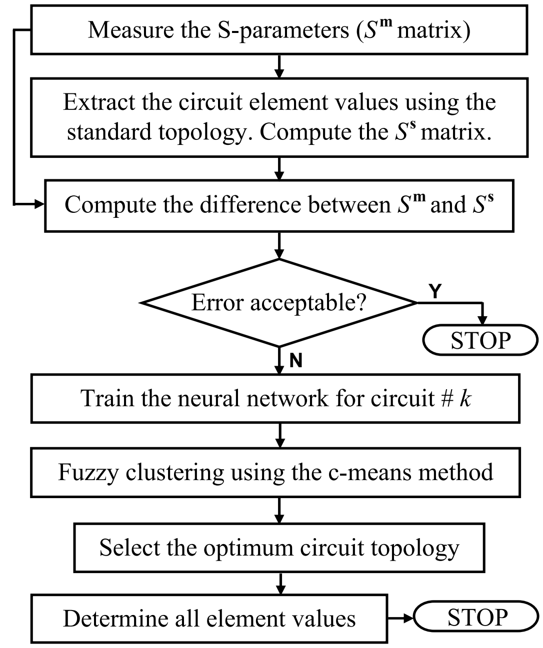

Fig. 11. Algorithm of the proposed method.

and v_i is the centroid of ith cluster,

$$v_i = \left(\sum_{k=1}^{N}(u_{ik})^h x_k\right)\left(\sum_{k=1}^{N}(u_{ik})^h\right)^{-1} \tag{3}$$

Therefore, for any circuit # k (k = 1, …, 5), the related $S^{\mathbf{k}}$ matrix would be compared to the input $S^{\mathbf{m}}$ matrix and each element of the two resulting 2x2 error matrices $E^{\mathbf{k, Re}}$ and $E^{\mathbf{k, Im}}$,

$$E_{ij}^{\mathbf{k,Re}} = \mathrm{Re}\left(S_{ij}^{\mathbf{k}} - S_{ij}^{\mathbf{m}}\right) \qquad i,j = 1,2 \tag{4}$$

$$E_{ij}^{\mathbf{k,Im}} = \mathrm{Im}\left(S_{ij}^{\mathbf{k}} - S_{ij}^{\mathbf{m}}\right) \qquad i,j = 1,2 \tag{5}$$

would receive a score scaled from 1 to 10 depending on its value. Thus, topology #k with smallest $E^{\mathbf{k,m}}$,

$$E^{\mathbf{k,m}} = \sum_{i=1}^{2}\sum_{j=1}^{2}\left\{\left[\mathrm{Re}\left(S_{ij}^{\mathbf{k}} - S_{ij}^{\mathbf{m}}\right)\right]^2 + \left[\mathrm{Im}\left(S_{ij}^{\mathbf{k}} - S_{ij}^{\mathbf{m}}\right)\right]^2\right\} \tag{6}$$

i.e., smallest score, would be selected as the most adequate circuit. In the above equation, Re(*) and Im(*) denote the real part and the imaginary part respectively. However, since the approach has to be generic, there is *no prior* knowledge on the input parameters, and then, it is impossible to compute numerically (6). Let $\{\Omega^{\mathbf{s}}\}$ be the set of $P_{\mathbf{s}}$ elements $\Omega_p^{\mathbf{s}}$ (p = 1, …, $P_{\mathbf{s}}$) in the standard circuit topology. A symbolic code was developed using [15] to analytically derive the following nonlinear functions

$$S_{ij}^{\mathbf{k}} = f_{ij}^{\mathbf{k}}\left(S_{ij}^{\mathbf{s}}, \{\Omega^{\mathbf{k}}\}\right) \quad i,j = 1,2 \quad k = 1, \ldots, 5 \tag{7}$$

in order to evaluate the alternative fuzzy criteria

$$E^{\mathbf{k,s}} = \sum_{i=1}^{2}\sum_{j=1}^{2}\left\{\left[\mathrm{Re}\left(S_{ij}^{\mathbf{k}} - S_{ij}^{\mathbf{s}}\right)\right]^2 + \left[\mathrm{Im}\left(S_{ij}^{\mathbf{k}} - S_{ij}^{\mathbf{s}}\right)\right]^2\right\} \quad (8)$$

The above relations depend *only* on the values of the $P_{\mathbf{k}}$ elements of set $\{\Omega^{\mathbf{k}}\}$ which represent the elements added to the standard topology to form circuit #*k*. Since (8) are strongly interdependent, highly nonlinear, and require a huge combination of values to be accurately evaluated, we used neural networks (NN) to learn these quantities. Let **x** be an *n*-vector $\{x_i, i = 1, \ldots, n\}$ containing the inputs and **y** be an *m*-vector $\{y_r, r = 1, \ldots, m\}$ containing the outputs from the output neurons. The original problem can be expressed as $\mathbf{y} = \boldsymbol{f}(\mathbf{x})$, while the neural network model for the problem is

$$\mathbf{y}_{NN} = \tilde{\mathbf{y}}(\mathbf{x}, \mathbf{w}) \;, \quad (9)$$

where **w** is a N_w-vector $\{w_i, i = 1, \ldots, N_w\}$ containing all the weight parameters representing the connections in the NN. The definition of **w** and the way in which $\mathbf{y}_{NN}$ is computed from **x** and **w** determines the structure of the NN. The most commonly used NN configuration is the Multi Layer Perceptrons (MLP). For such an *L*-layer neural network, the function given by (9) is calculated on the basis of the input layer L_1 while using [16]

$$z_i^1 = x_i\,, \quad i = 1, \ldots, N_1, \quad n = N_1 \quad (10)$$

z_i^1 is the output of the i^{th} neuron of the input layer, and while proceeding layer by layer, the output of layer L_l is given by the activation function σ as

$$z_j^l = \sigma\left(\sum_{k=0}^{N_{l-1}} w_{jk}^l\, z_k^{l-1} + w_{j0}^l\right), \quad (11)$$

where $j = 1, \ldots, N_l$, and $l = 1, \ldots, L$, to reach the output layer that gives

$$y_k = z_k^L\,, \quad k = 1, \ldots, N_L, \quad m = N_L \quad (12)$$

In these relations, N_l is the number of neurons in layer L_l, w_{jk} represents the weight of the connection between the k^{th} neuron of the layer L_{l-1} and the j^{th} neuron of the layer L_l. By allocating values to the standard $S^{\mathbf{s}}$ parameters and varying the value of each element $\Omega_p^{\mathbf{k}}$ ($p = 1, \ldots, P_{\mathbf{k}}$) of set $\{\Omega^{\mathbf{k}}\}$, we utilized (7) to compute the $S^{\mathbf{k}}$ parameters and therefore, the difference $\{S^{\mathbf{k}} - S^{\mathbf{s}}\}$. The resulting data in the form of

$$Tr^{\mathbf{k}} = \left[\underbrace{\mathrm{Re}\left(S_{ij}^{\mathbf{k}} - S_{ij}^{\mathbf{s}}\right), \mathrm{Im}\left(S_{ij}^{\mathbf{k}} - S_{ij}^{\mathbf{s}}\right)}_{8\text{ inputs } (i,j=1,2)}, \underbrace{\Omega_1^{\mathbf{k}}, \ldots, \Omega_{P_{\mathbf{k}}}^{\mathbf{k}}}_{p_{\mathbf{k}}\text{ outputs}}\right] \quad (13)$$

was submitted to a three-layer NN structure for training using the *Neuromodeler* tool [17].

The input layer has 9 neurons (the 4 real and 4 imaginary parts in (8) and the operating frequency *f*) while the output layer contains $P_{\mathbf{k}}$ neurons. The hidden layer is composed of 22 to 45 neurons depending on the circuit data file under training.

Prior to further discussion, two points had to be considered in this work. First, the input parameter space is of high-dimension and the step sizes should be small enough to assure good convergence. This will lead to a too large number of combinations of input parameters. Second, even after selecting the optimum topology, the values of the elements of set $\{\Omega^{\mathbf{s}}\}$ obtained after the first round of extraction, i.e., using the standard topology need to be tuned in the final circuit along with the neural outputs, i.e., the elements of set $\{\Omega^{\mathbf{k}}\}$. An optimization loop is then essential. Therefore, instead of generating large data files required for a classical neural development, we used the values of the following vector

$$\Omega = \left[\Omega_1^{\mathbf{k}}, \ldots, \Omega_{P_{\mathbf{k}}}^{\mathbf{k}}, \Omega_1^{\mathbf{s}}, \ldots, \Omega_{P_{\mathbf{s}}}^{\mathbf{s}}\right] \quad (14)$$

as starting vector for the optimization loop. This procedure will assure better and faster convergence.

3 Circuit Level: Proposed Approach

Once the optimum topology is selected, the transistor can be plugged into a circuit for efficient design. To further investigate the capabilities of neural networks to predict the circuit performance, we built a PKI NN [18]. Since PKI uses empirical *prior knowledge* mapping between inputs and outputs to learn better and faster the behavior of a given multi-stage circuit, the purpose is to reduce significantly the circuit simulation process, the computing time and the required training data as well as to enhance the model prediction beyond the training range [16]. This enhancement allows us to efficiently predict the performance of a circuit with 3- or more stages based on the training of its first and second stage input-output relationships.

4 Validation

The first MESFET device to be characterized is the one reported in [15] using topology # 4. Since in this paper all values are given as well as the final error between measured and simulated *S*-parameters, a reliable comparison can be achieved for a full validation. In fact, by comparing the S-parameters (Fig. 13) and the element values (Table I) in [15] with those obtained in 2.3 seconds using our technique, FET circuit # 4 achieved a very close agreement as expected, with a smaller error, defined for a set of N_f selected frequency values f_q ($q = 1, \ldots, N_f$) as [15]

$$E^{\mathbf{k},\mathbf{m}} = \sum_{q=1}^{N_f} \sum_{i=1}^{2} \sum_{j=1}^{2} \left| 1 - \frac{S_{ij}^{\mathbf{k}}\left(f_q\right)}{S_{ij}^{\mathbf{m}}\left(f_q\right)} \right|^2 \tag{15}$$

The second device is FET EPA018A. After 2.1 seconds, our method showed that circuit # 3 is the most appropriate (Fig. 14) with a final error of 1.8%, smaller than the input user specifications, i.e., 2%.

The third device is an HBT proposed in [5] with topology # 2. A similar close agreement is shown with published results (Fig. 15 and Table II).

Finally, a three-stage amplifier was designed and simulated in [10]. The PKI input vector **x** contains the input power, the DC bias, and the frequency. The output vector **y** contains the output power of the two first harmonics. Based on one- and two-stage training data, a PKI NN showed a better agreement with data simulated in [10] than those given by a MLP NN for the three-stage amplifier. Therefore, a better prediction was achieved in 0.2s compared to the 12s required for the simulation in [10].

5 Conclusion

In this paper, an efficient CAD tool was presented that combines fuzzy and neural capabilities to first determine the optimum small-signal FET/HBT equivalent circuit topology, and then, to efficiently predict a circuit performance. The method has been proven to be fast and accurate and can be applied to other RF/microwave active devices and circuits.

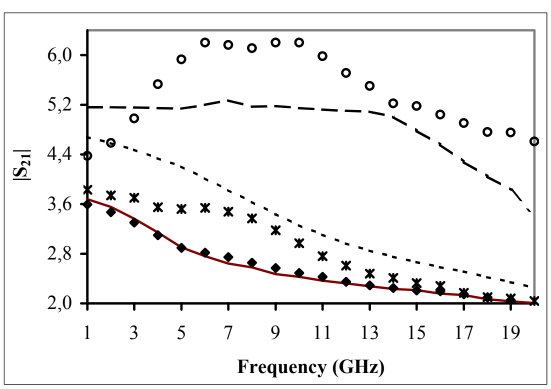

Fig. 13. Comparison of measured S_{21}-parameters (♦) with those extracted using different topologies: ---- : topology # 1, —— : topology # 2, **o** : topology # 3, —— : topology # 4, ***** : topology # 5.

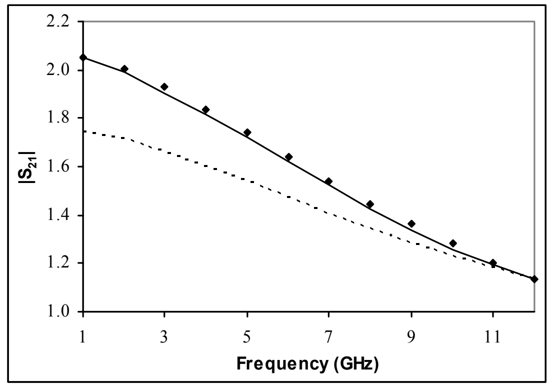

Fig. 14. Comparison of Measured S_{21}-Parameters (♦) with those extracted using different topologies: ---- : topology # 1, —— : topology # 3.

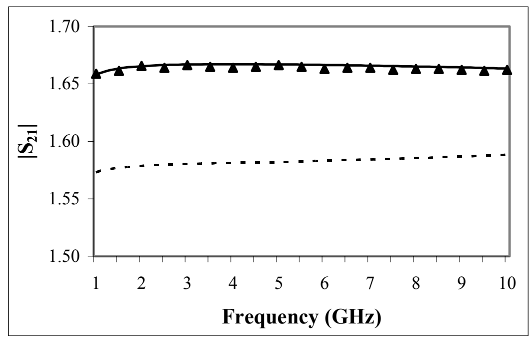

Fig. 15. Comparison of Measured S_{21}-Parameters (♦) with those extracted using different topologies: ---- : topology # 1, —— : topology # 2.

Table I. Comparison between the MESFET parameters reported in [14] and our results.

	Circuit # 4	Our Values
C_{gs} (pF)	0.277	0.215
C_{gd} (pF)	0.0207	0.0211
C_{ds} (pF)	0.0993	0.101
g_m (mS)	26.9	27.3
τ (ps)	1.22	1.25
R_i (Ω)	15.3	15.1
R_{gd} (Ω)	43.8	43.6
R_{ds} (Ω)	215	218
R_g (Ω)	8.9	9.1
R_s (Ω)	7.5	7.3
R_d (Ω)	13.6	13.2
L_s (nH)	0.437	0.441
L_d (nH)	0.452	0.447
L_g (nH)	0.254	0.258
C_{gsp} (pF)	0.0409	0.0397
C_{gdp} (pF)	0.001	0.001
Error (%)	8.4	2.9

Table II. Comparison between the HBT parameters reported in [5] and our results.

	Circuit # 2	Our Values
R_e (Ω)	1	1.7
L_e (pH)	7.5	8.5
R_b (Ω)	0	0
L_b (pH)	15	14.3
R_c (Ω)	1	1.8
L_c (pH)	5	3.1
C_{be} (fF)	3.4	3.0
C_{bc} (fF)	81	73.4
α_o	0.98	0.94
τ (ps)	2.4	1.9
R_{be} (Ω)	95.2	99.9
R_{bc} (Ω)	6.79	7.28
R_{b1} (Ω)	1.85	1.62
C_{bep} (fF)	30	30.2
C_{cep} (fF)	30	30.1
C_{bcp} (fF)	0	0

Table III. Three-stage fundamental {Pout (ω)} and second harmonic output power {Pout (2ω)}: Comparison between simulated results given by [10] and those from MLP and PKI neural networks, trained with 1- and 2-stage output power data.

	P_{out} (ω)	P_{out} (2ω)
ADS [10]	-76.675	-191.05
PKI	-76.676	-190.31
MLP [17]	-76.602	-189.91

Acknowledgement
This work is supported in part by Natural Science and Engineering Research Council of Canada.

References:

[1] J.M. Golio, *Microwave MESFETs and HEMTs*, Boston: Artech House, 1991.
[2] L. Fujiang, G. Kompa, "FET model parameter extraction based on optimization with multiplane data-fitting and bidirectional search-a new concept," *IEEE Trans. Microwave Theory Tech.*, Vol. 42, 1994, pp. 1114-1121.
[3] C. Van Niekerk & *al.*, "A robust integrated multibias parameter-extraction method for MESFET and HEMT models," *IEEE Trans. Microwave Theory Tech.*, Vol. 48, 2000, pp. 777-786.
[4] G. Dambrine & *al.*, "A new method for determining the FET small-signal equivalent circuit," *IEEE Trans. Microwave Theory Tech.*, Vol. 36, 1988, pp. 1151-1159.
[5] P.J. Tasker, M. Fernandez-Barciela, "HBT small signal T and π model extraction using a simple, robust and fully analytical procedure", *IEEE MTT-S Int. Symp.*, 2002, pp. 2129–2132.
[6] L. Ji, M.C.E. Yagoub "Combined fuzzy-neural approach for optimal RF/microwave transistor modeling," *WSEAS Int. Conf. on Electronics, Hardware, Wireless Optical Communications*, Salzburg, Austria, 2005.
[7] R. Menozzi & *al.*, "Small-signal modeling for microwave FET linear circuits based on a genetic algorithm," *IEEE Trans. Circuits and Systems*, Vol. 43, 1996, pp. 839-847.
[8] M. Fernandez-Barciela & *al.*, "A simplified broad-band large-signal nonquasi-static table-based FET model," *IEEE Trans. Microwave Theory Tech.*, Vol. 48, 2000, pp. 395-405.
[9] R. Anholt, S. Swirhun, "Equivalent-circuit parameter extraction for cold GaAs MESFET's," *IEEE Trans. Microwave Theory Tech.*, Vol. 39, 1991, pp. 1243-1247.
[10] ADSv.2003, *Agilent Technologies*, Palo Alto.
[11] J.M.M. Rios & *al.*, "A self-consistent method for complete small-signal parameter extraction of InP-based heterojunction bipolar transistors", *IEEE Trans. Microwave Theory Tech.*, Vol. 45, 1997, pp. 39-45.
[12] B. Sheinman & *al.*, "A peeling algorithm for extraction of the HBT small-signal equivalent circuit", *IEEE Trans. Microwave Theory Tech.*, Vol. 50, 2002, pp. 2804-2810.
[13] T.H. Teo & *al.*, "Systematic direct parameter extraction with substrate network of SiGe HBT", *Radio Frequency Integrated Circuits Symp.*, 2004, pp. 603-606.
[14] M.K. Ahmed, S.M.M. Ibrahem, "Small signal GaAs MESFET model parameters extracted from measured S-parameters," *National Radio Science Conf.*, Cairo, Egypt, 1996, pp. 507-515.
[15] *Maple V reference manual*, New-York.
[16] Q.J. Zhang, K.C. Gupta, *Neural Networks for RF and Microwave Design*, Norwood: Artech House, 2000.
[17] *NeuroModeler Version 1.02*, Prof. Q.J. Zhang, Carleton University, Ottawa, ON, Canada.
[18] P.M. Watson & *al.*, **"**Development of knowledge based artificial neural network models for microwave components,**"** *IEEE MTT-S Int. Symp.*, 1998, pp. 9-12.