JOURNAL OF AUTOMATIC CONTROL, UNIVERSITY OF BELGRADE, VOL 16:25-28, 2006 ©

Neural Network for Noise Modeling of SiGe HBT's

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Abstract – **The advantages of SiGe HBTs make them very promising for modern RF communication systems and therefore their noise performance becomes an important issue as well. This paper presents the noise modeling of SiGe HBTs for broad operating ranges. Two neural network structures are presented and discussed from the aspect of modeling accuracy: a basic one and an extended one obtained by adding the S-parameters to the input**

Index Terms – **Artificial neural networks, PKI networks, noise parameters, SiGe HBT.**

I. INTRODUCTION

HETEROJUNCTION bipolar transistors (HBTs) are widely used for the RF and high speed applications. First commercial HBT was made of AlGaAs/GaAs material and that composed material was used very often earlier. The range of modern HBT transistor is wide and the most attractive for RF application are SiGe/Si HBT, InGaAs/InP HBT, InGaP/GaAs HBT, etc

Silicon-Germanium (SiGe) technology is the driving force behind the explosion in low-cost, lightweight, personal communications devices like digital wireless handsets, as well as other entertainment and information technologies like digital set-top boxes, Direct Broadcast Satellite (DBS), automobile collision avoidance systems, and personal digital assistants. SiGe extends the life of wireless phone batteries, and allows smaller and more durable communication devices. The heart of SiGe technology is a SiGe heterojunction bipolar transistor (HBT). Another advantage of SiGe technology is the capability to be integrated in CMOS circuits, enabling production of cheap high-performance BiCMOS integrated circuits. Products combining the capabilities of cellular phones, global positioning, and Internet access in one package, are being designed using SiGe technology. These multifunction, low-cost, mobile client devices capable of communicating over voice and data networks represent a key element of the future of computing. Therefore, SiGe technology is the one idea whose time is comming [1].

For the design and optimisation of microwave circuits based on HBTs, it is essential to use an appropriate HBT model for simulating circuit performances. Standard DC models of HBTs are based on modificated physical models of bipolar transistor - BJTs. A drawback of the models based primarily on the physical background is the existence of too many coefficients that are difficult to extract. Most of the existing small-signal models are mostly based on a device equivalent circuit representation. Elements of the equivalent circuit are optimized in order to fit measured characteristics of the device being modeled. However, it should be noted that a chosen equivalent circuit may not be adequate over the whole range of operating frequencies. In addition, the values of equivalent circuit elements have to be extracted for any new bias point. However, as frequency increases the complexity of the equivalent circuit increases as well because additional parasitic effects have to be taken into account.

During the last years, from the the aspect of efficiency, accuracy and simplicity, neural network approach has been considered to be a good solution for microwave device modeling [2],[3]. The neural network approach has recently been proposed for modeling of microwave transistors for both small-signal and large-signal applications, but there are still not too many published results in this field. Most of them are related to the standard microwave FETs (MESFETs and HEMTs) [4]. The authors' results related to the development of DC and small-signal neural models of HBTs have been presented in [5] and [6].

An important condition for successful design of low noise communication device is the availability of efficient and accurate noise model of HBTs which represents an efficient alternative to expensive and complex measurements. Though, the developed physical and empirical HBT noise models as well as DC and small signal models have numerous limits.

Having in mind the complexity of HBT noise mechanisms, neural networks, able to model highly nonlinear relations between two different data sets, seem to be an efficient and accurate tool for HBT noise parameter modeling, suitable for fast CAD purposes. Therefore, in this paper, we suggest using of the ANNs for predicting noise parameters of the device over the whole frequency and bias ranges [6] . To authors' knowledge, artificial neural network approach has not yet been used by other authors for the noise modeling of HBTs.

In this paper a basic noise model of SiGe HBT with three neurons in the input and four neurons in the output layers is presented first. A modified and improved basic ANN noise model with eight neurons corresponding to the magnitudes and angles of HBT S-parameters added to the input layer is presented as the main part of this paper. It is shown that introducing additional inputs to the basic network can enhance the accuracy of the neural models. Both neural models that are proposed in this paper are valid for the noise modeling of SiGe HBT for small-signal applications.

II. NOISE MODELING OF SIGE HBT

ANN-based noise modeling for a NEC SiGe HBT, type NSGH2031M05, is presented here. A training and test sets are generated from the available experimental data for device, [7].

A schema of the ANN network configuration for noise modeling of SiGe HBT is shown in Fig. 1. The proposed

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basic noise model is a multilayer perceptron (MLP) network consisting of neurons grouped into four layers: one input, one output and two hidden layers. There are three neurons in the input layer that correspond to the DC bias V_{ce}, DC collector current I_c, and frequency *f*. The four neurons in the output layer correspond to the minimum noise figure $F_{\min}$, magnitude of the optimum reflection coefficient |Γopt|, angle of the optimum reflection coefficient ∠Γopt , and normalised equivalent noise resistance $R_n / 50$.

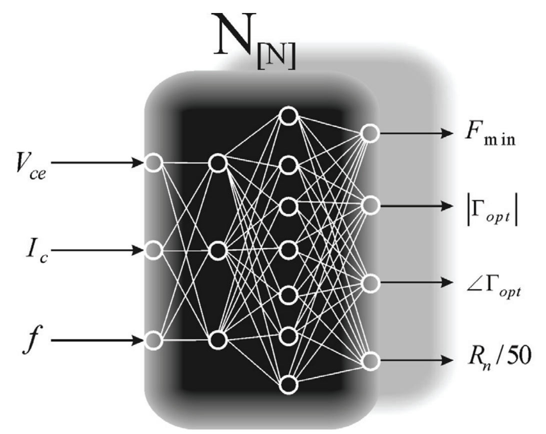

Figure 1. *Basic neural HBT noise model (an example of internal MLP structure is shown)*

Details of training and test procedure as well as obtained results using the basic noise model are presented in the earlier authors' paper [6].

With the aim to improve additionally the accuracy of the ANN noise model described above, its structure was modified in such way that eight neurons corresponding to the magnitudes and angles of HBT S-parameters for given frequency and bias conditions were added to the input layer. Considering the fact that there is corelation between noise and S-parameters of transistors, the main aim of this model is to use this prior knowledge about the device S-parameters as additional inputs into the ANN model in order to increase the modeling accuracy. Defined in that way, the proposed model can be regarded as a kind of a prior knowledge input PKI (*prior knowledge input*) models. Similar PKI ANN model has been applied to improve noise modeling of MESFET/HEMT microwave transistors, [8], but only for the noise parameters not modeled accuratelly by the basic ANN model.

A black-box schema of the modified neural HBT noise model is shown in Figure 2. Eleven neurons in the input layer correspond to the following values: DC bias V_{ce}, DC collector current I_c, frequency f, and magnitudes and angles of HBT S_{11}, S_{12}, S_{21} and S_{22} parameters. Like previous model, four neurons in the output layer corespond to the minimum noise figure $F_{\min}$, magnitude of the optimum reflection coefficient |Γopt|, angle of the optimum reflection coefficient ∠Γopt , and normalised equivalent noise resistance $R_n / 50$.

The available trainig and test set of noise data referred to 33 discrete frequency points covering the operating range, (2-18) GHz. At each frequency point, noise parameter data referred to the following combinations of DC collector-emitter voltages V_{ce} and DC collector currents I_c, respectively: (2V, 3mA), (2V, 5mA), (2V, 20mA), (3V, 3mA) and (3V, 5mA). It is easy to calculate that there are 165 different combination of bias points and discrete frequency points, i.e. samples.

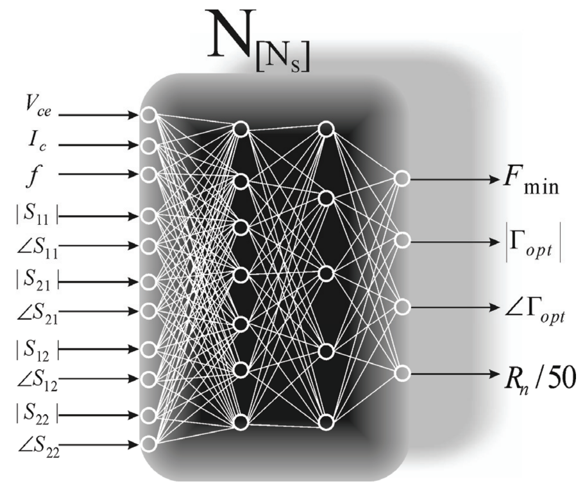

Figure 2. *Modified neural HBT noise model*

The training set was obtained by selecting 132 samples. In order to check the generalization capability, a test set containing 33 remained samples was used. These samples refered to whole frequency range from 2 to 18 GHz and to one DC bias point $V_{ce} = 2V$, $I_c = 5mA$.

Several proposed multilayer perceptron (MLP) network configuration with different number of neurons in two hidden layer were trained using the same training set. The minimum and maximum numbers of neurons in hidden layers have been selected on the basis of the trial training of several neworks with different number of hidden neurons. The best results gave neural network configurations with the number of hidden neurons between 1 and 10 neurons for the first hidden layer and between 2 and 10 for the second hidden layer. Therefore, in order to obtain neural model with accuracy as best as possible, 90 different neural network configuration were trained. After the training procedure, comparing all 90 models, the best neural network was selected.

In the example shown in this paper, activation functions of the ANN neurons are linear for input and output neurons and sigmoid for hidden neurons. The neural networks were trained using the *Levenberg-Marquardt* back-propagation algorithm. The number of training epochs was limited to a maximum 180 for each network.

Therefore, in this research triple training process on each neural network has been performed with the aim to achieve better accuracy of the model.

When the initial values of the network parameters were set randomly, as it was the case, the reperated training process of the same network structure do not result in the same modeling performances. Therefore, in this research triple training process of each neural network structure were performed with the aim to achieve better accuracy of the model, i.e. the total number of trained neural networks was $3\times90=270$. The time needed for the training process on a Pentium 4 with processor declared on 2500+ and 512MB RAM was one hour.

III. MODELING RESULTS

After the training process, noise parameters were simulated by the all developed neural models for both input values used in the training procedure, i.e. from the training set, and test input values outside the training set. In order to compare the accuracy of the models, the average test error (ATE [%]), the worst-case error (WCE [%]), and the *Pearson Product-Moment* correlation coefficient (r) between the measured and simulated data were calculated. On the basis of three above-mentioned criteria, the results were compared and the model marked as 1M4_7_5 was selected as the best model. The model's notation shows that the neural network has four layers and 7 neurons in the first and 5 neurons in the second hidden layer, regarded from input to output. The number "1" denotes the first successive training of the same network.

The error statistics for the selected model is presented in Table 1. The average error and worst-case error are given for both input data belonging to the training set and input data belonging to the test set. It could be seen that the value of ATE is less than 0.836%, and the value of WCE is less than 2.868%. The correlation coefficient r is greater than 0.99. It can be seen that the values of errors are satisfactorily low even in case when input parameters are outside of the training data.

For the comparison purpose, the average and worst case errors for the earlier-developed basic model marked as 3M4_3_7, [6], (Fig 1) are presented in the Table 1 as well. The subtraction of the average and worst case errors between the proposed and basic neural model are presented in the Table 1. It can be observed that, compared to the basic neural model, the accuracy of modelling is improved by using the proposed neural model.

As an illustration, Fig. 3 shows the plots of noise parameters versus frequency, obtained by the chosen neural model 1M4_7_5, at two different bias points: (1) a training bias point ($V_{ce}=2\text{V}$, $I_c=5mA$) and (2) a bias point that does not belong to the training set ($V_{ce}=2V$, $I_c=20mA$). For the comparison purpose, the corresponding measured data are shown as well. An excellent agreement of simulated noise characteristics with measured values can be observed. Furthermore, it can be seen that, for inputs outside the training set, there is an excellent agreement of the values simulated by the proposed model with the measured ones. That shows that the developed neural model has a good generalization ability.

In order to simulate noise parameters using modified neural model for any combination of frequency and bias condition point within the transistor's operating range, the coresponding magnitudes and angles of SiGe HBT *S* parameters are needed. For this purpose, the previously developed MLP (Multi-Layer Perceptron) neural model [6] that can predict magnitudes and angles of all four S parameters of SiGe HBTs for any frequency and bias condition was used.

IV. CONCLUSION

The obtained results show that the neural network approach can be used as an efficient tool for noise modeling of SiGe HBT transistors very convenient for CAD purposes.. Introducing S-parameters into the model input increases model accuracy, while the model is still characterized by the efficiency and simplicity.

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Table 1 *Error statistics for two ANN models 1) 1M4_7_5 and 2) 3M4_3_7*

		ATE1[%]:	ATE1[%]-ATE2[%]:	WCE1[%]:	WCE1[%]-WCE2[%]:	r1:
Training data	$F_{\min}$	0.386	-0,157	1.385	-0,41	0.9998
	$\vert\Gamma_{opt}\vert$	0.601	-0,134	2.868	-0,136	0.9996
	$\angle\Gamma_{opt}$	0.228	-0,092	2.106	-1,808	0.9999
	$R_n/50$	0.149	-0,123	0.858	-1,462	0.9999
Test data	$F_{\min}$	0.537	-0,164	1.575	-1,043	0.9997
	$\vert\Gamma_{opt}\vert$	0.836	-0,073	2.412	-0,886	0.9997
	$\angle\Gamma_{opt}$	0.256	-0,140	0.799	-0,521	0.9999
	$R_n/50$	0.388	-0,134	1.898	+0,715	0.9999

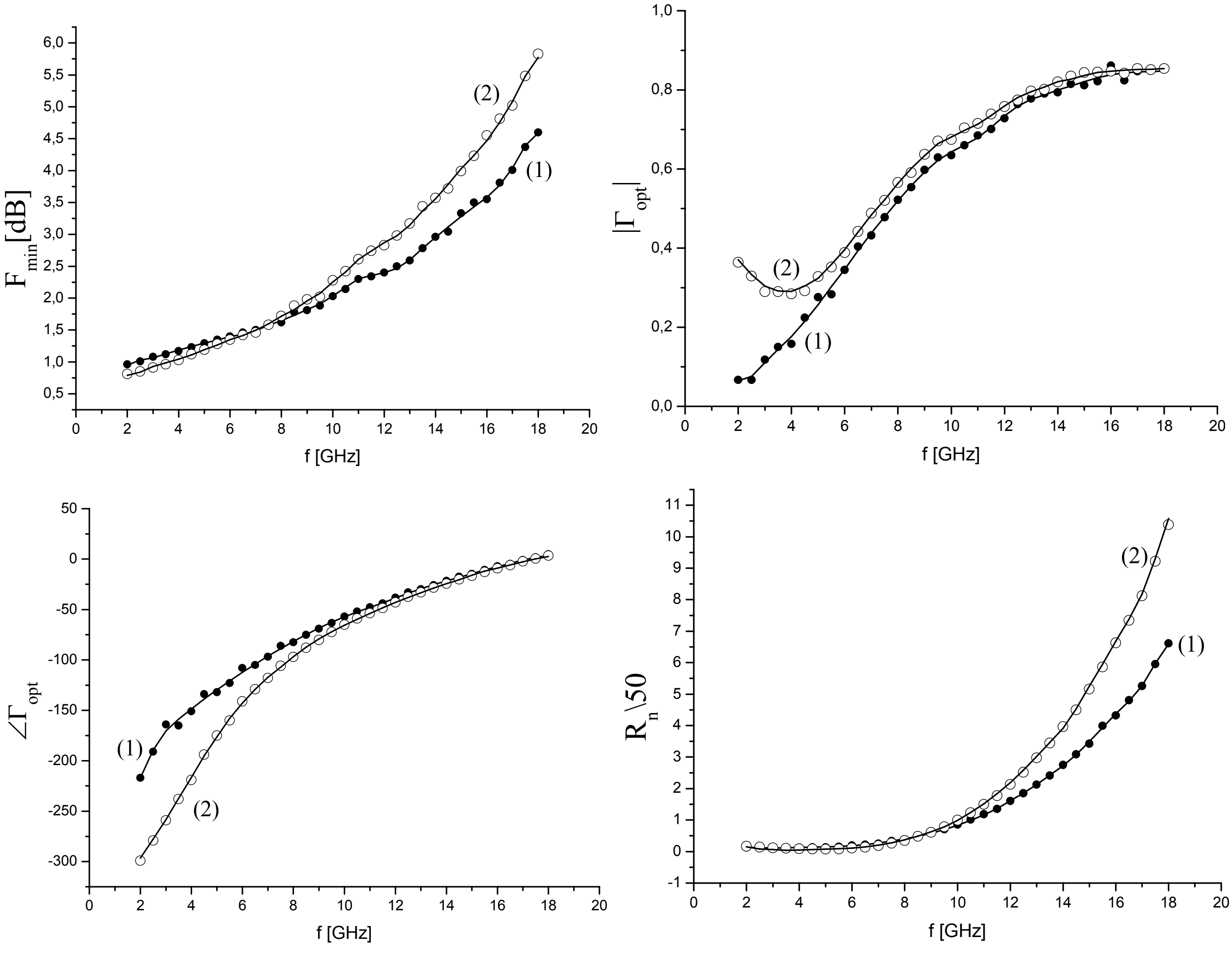

Figure 3. *Noise parameters versus frequency values obtained by model 1* $N_{[N]}$ *7_5 (continual curves); measured values (symbols)*: *(1)* $V_{ce} = 2V$, $I_c = 20mA$; *(2)* $V_{ce} = 2V$, $I_c = 5mA$