Small-Signal Models of Heterojuction Bipolar Transistors Based on Neural Networks

Vera Marković, Aleksandar Stošić

Abstract: **Heterojunction bipolar transistors are considered to be a promising technology in microwave wireless communications. A convenient approach for small-signal modeling of heterojunction bipolar transistors based on neural networks is presented in this paper. Developed neural models enable an efficient prediction of device S parameters over the whole frequency range and over the broad ranges of operating conditions. Testing on the input data not used in the training procedure shows good accuracy of the model.**

Keywords - **Heterojunction bipolar transistors, small-signal models, neural networks**

I. Introduction

Heterojunction Bipolar Transistors (HBT) have become very promising devices for different applications at the microwave and millimeter-wave frequencies [1], [2]. For example, HBT's are used for power amplifiers as well as for low noise amplifiers in mobile communication systems. This device tecnology is considered as very convenient for RF front-end circuits in next-generation wireless communications.

Important condition for any successful design work is the availability of efficient and accurate device models. During the last decade a tremendous work has been done for developing physical and empirical HBT models [3],[4]. Despite this fact, we still do not have an unified, accurate model standard for HBTs. The main reason is that the device physics is very complicated and the range of operating conditions is broad. The existing models based primarily on the physical background are inconvenient because of too many coefficients that are difficult to extract. The other models are mostly based on the traditional optimisation techniques or on the direct extraction of the equivalent circuit elements.

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 [5]. As highly nonlinear structures, neural networks are able to model nonlinear relations between two different data sets. Once trained, the neural model provides fast response for different input vectors that in principle can cover the whole operating range. A very important property of neural networks is generalisation capability [6], which provides sufficiently accurate response for different input vectors not included in the training set, without additional computational efforts or new measurements.

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). The authors' results related to the development of small-signal and noise neural models of MESFETs and HEMTs have been presented in [7]-[9]. On the other hand there are only a few published results in the area of HBT modeling by using the neural network approach [10].

In this paper, the development of neural models for AlGaAs/GaAs HBTs is presented. The attention is paid to small-signal HBT applications. The neural models enable an efficient prediction of transistor's S parameters over the wide frequency and bias condition ranges.

II. Advantages of the HBT's for Wireless Communication Applications

The heterojunction bipolar transistors are composed of two different semiconductor materials with different band gap widths [11]. $Al_xGa_{1-x}As/GaAs$ npn structure is used very often and its application has matured to commercial level. A heavily doped n+ GaAs layer is grown first for the collector contact, followed by a lightly doped n GaAs layer for the collector. A heavily doped p+ GaAs layer is used for the base. Again, a wide-band-gap AlGaAs layer is grown for the emitter. Heavily doped n+ GaAs layer is grown to facilitate the fabrication of low-resistance ohmic contacts.

High injection efficiency is obtained in HBTs by using a material with a larger energy band gap for the emitter than that used for the base material. The large energy band-gap emitter blocks injection of holes from the base. Therefore, the doping concentration in the base and emitter can be adjusted over a wide range with little effect on injection efficiency. Thereby, HBT can provide good current gain simultaneously keeping lower base resistance and parasitic capacitance than conventional bipolar transistors**.** Due to this advantages, HBT provide a cutoff frequency f_T over 100 GHz. Hence, in comparison with Si bipolar junction transistors (BJTs), HBTs show better performance in terms of emitter injection efficiency, base resistance, base-emitter capacitance, and cutoff frequency. They also offer good linearity, low phase noise and high power-added efficiency. Due to good linearity properties in operational rating, HBT could be used in RF amplifiers for mobile communication.

In comparison with field effect transistors, HBT processing requires less demanding lithography, therefore, HBTs can cost

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less to fabricate and can provide improved lithographic yield. This technology can also provide higher breakdown voltages and easier broad-band impedance matching.

III. Modeling of the HBT S Parameters Using Neural Networks

The HBT data that can be found in the manufacturer's data sheets are mostly limited to a number of discrete frequency points and, in the best cases, at a few bias conditions. On the other hand, reliable and accurate models of HBTs for whole frequency operating range and for wide bias condition ranges are required for the optimisation and design of microwave active circuits based on HBT technology. In this paper, neural network models are presented that can predict magnitudes and angles of all four S parameters of HBTs for any frequency and bias condition point within the transistor's operating range. For this purpose, a MLP (Multi-Layer Perceptron) network structure [6] has been used. The network has four layers: one input layer, two hidden layer, and one output layer. The number of neurons in the input and output layers is determined by the chosen number of input and output parameters. In this case, there are three neurons in the input layer that correspond to the DC bias V_c, DC base current I_b, and frequency *f*, and eight neurons in the output layer that correspond to the magnitudes and angles of the scattering parameters.

Neural network has been trained using a back-propagation algorithm [6]. A training set could be obtained by measurements, or from the simulation by using some other, often very complex model that requires much efforts and time. It is very important that the whole operating range of the device is adequately covered by the training set data. In this research a training set is generated by using the experimental data.

In principle, there are two approaches for the selection of number of neurons in hidden layers. The first approach is to perform the training procedure with a fixed number of neurons that is chosen in advance. The second one is to train several neural networks with different number of neurons in the hidden layers and select the best neural network comparing all models. In this research we have used the second approach.

In order to compare models' accuracy, average test error (ATE [%]), worst-case error (WCE [%]), and the *Pearson Product-Moment* correlation coefficient (r) between the referred and the modeled data have been calculated. The correlation coefficient indicates how well the modeled values match the referent values, i.e. a value near 1 indicates an excellent predictive ability. It is important to note that the test procedure has been done not only for the data from the training set, but also for the data that are not used in the training process, with the aim to check the generalization capability of developed neural networks.

IV. Modeling Results

In this research we have modeled six different AlGaAs HBT's, within 0.05÷40 GHz frequency range. The data for training sets that we used in modeling procedure had been obtained by collaboration with a microwave laboratory at Northeastern University, Boston, USA, where HBT S-parameter measurements were performed.

With the aim to illustrate the effectiveness and accuracy of neural modeling procedure, the results for a HBT device marked as HBT40020-002-8 are presented here. The total number of S parameters data used in training and test procedure for the selected HBT transistor was 5880. The data refers to the frequency range (0.05÷40) GHz. The frequency range was divided into four subranges as follows: first subrange (0.05÷0.5) GHz with 0.05 GHz step, second subrange (0.5÷1) GHz with 0.1 GHz step, third subrange (1÷10) with 1 GHz step, and fourth subrange (10÷40) GHz with 2 GHz step. Therefore, operating frequency range was covered with 35 discrete frequency points. S parameters were measured for different combination DC collector bias and base current in the whole frequency range. DC collector bias had the fallowing values: 1V, 3V, 4V, and DC base current had the fallowing values [μA]: 22, 39, 61 107, 195, 401 and 791. Therefore, the measurements were performed at 735 operating points and eight S parameter data (magnitudes and angles) correspond to each point: Mag(S_{11}), Ang(S_{11}), Mag(S_{12}), Ang(S_{12}), Mag(S_{21}), Ang(S_{21}), Mag(S_{22}) i Ang(S_{22}). Training set was obtained by extracting 595 data points from the measurement data. Therefore the training set contained 4760 S-parameters data. In order to check the generalization capability of neural network, a test set is generated from the rest of data points containing 1120 S-parameters data.

With the aim to avoid the errors caused by a rapid change of some S parameters angle characteristics between the values -180° and +180°, a conversion of the angle range from (-180÷180)° to the range (0÷360)° was performed.

Several neural networks with different number of hidden neurons were trained using the same training set. Number of hidden neurons varied between 9 and 16 neurons. The number of training epoch each network was limited on maximum 180. Time needed for training process on a Pentium 4 with processor declared on 2500+ and 512MB RAM was two hour and 15 minutes. However, once trained, the network provides fast response for different input vectors.

In order to improve the accuracy of neural models, multiplied training of the same network was performed. Namely, every new training process on the same neural network generates different errors. The reason for that is random setting of initial values of neural networks' weights and bias for each new training process. Therefore, in this research triple training process on each neural network has been performed with the aim to achieve better accuracy of the model. These models have then been applied to get the scattering parameter values for various bias values different from the ones used for training. The simulated results were compared with experimentally obtained data. On the basis of that, a model marked as 2M4_16_15 has been selected as the best model. The number 2 denotes second successive selected neural network training. The number 4 shows that the neural network has four layers. Numbers 16 and 15 denote the number of neurons in the first and second hidden layer, respectively.

As an illustration of selected model's accuracy, the scatter plots (correlation coefficient characteristics) for Mag(S) and

Angle(S) are shown in Fig. 1, where the outputs of the neural model are given on the Y axis and the experimental data are given on the X axis. It is important to note that the inputs in the neural model used for this calculation do not belong to the training set. It can be seen that simulated values match the measured data with a great accuracy forming linear correlation characteristics.

Fig. 2 shows the magnitudes and angles of all four S parameters versus frequency, obtained by using the chosen neural model, at four different bias points that have not been included in the training set:

(1) $V_c = 1V$, $I_b = 107\mu A$; (2) $V_c = 3V$, $I_b = 39\mu A$;

(3) $V_c = 3V$, $I_b = 195\mu A$; (4) $V_c = 4V$, $I_b = 107\mu A$.

For the comparison purpose, the corresponding experimental data are shown in the same figure. It can be seen that there is an excellent agreement of our model with the measured values. That shows that the developed neural model has a good generalisation ability.

V. Conclusion

The obtained results show that the neural network approach can be used as an efficient tool for small-signal modeling of HBT transistors. HBT neural models enable accurate prediction of magnitudes and angles of S parameters over the whole frequency range and over the broad ranges of operating conditions. In principle, some additional effects like the temperature could also be involved by including new neurons into the input layer and and by using appropriate training sets.

In comparison with other modeling approaches that could be applied for novel active devices used in modern communication systems, neural network approach has advantages from the aspect of simplicity, efficiency and accuracy. An insight into the physical operating mechanism is not necessary since a black-box approch is used. Neural network models provide simple and reliable prediction of device characteristics and can be easily implemented within the standard microwave circuit simulators.

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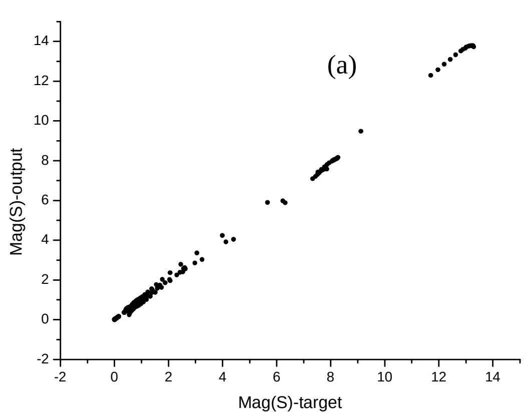

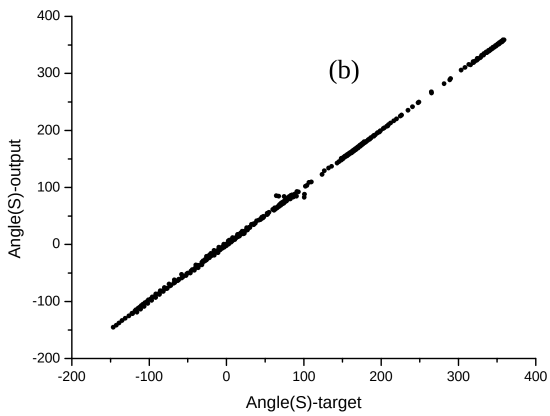

Figure 1. Scatter plots of the neural network output data versus the experimental (target) data:(a) magnitude and (b) angle of S parameters

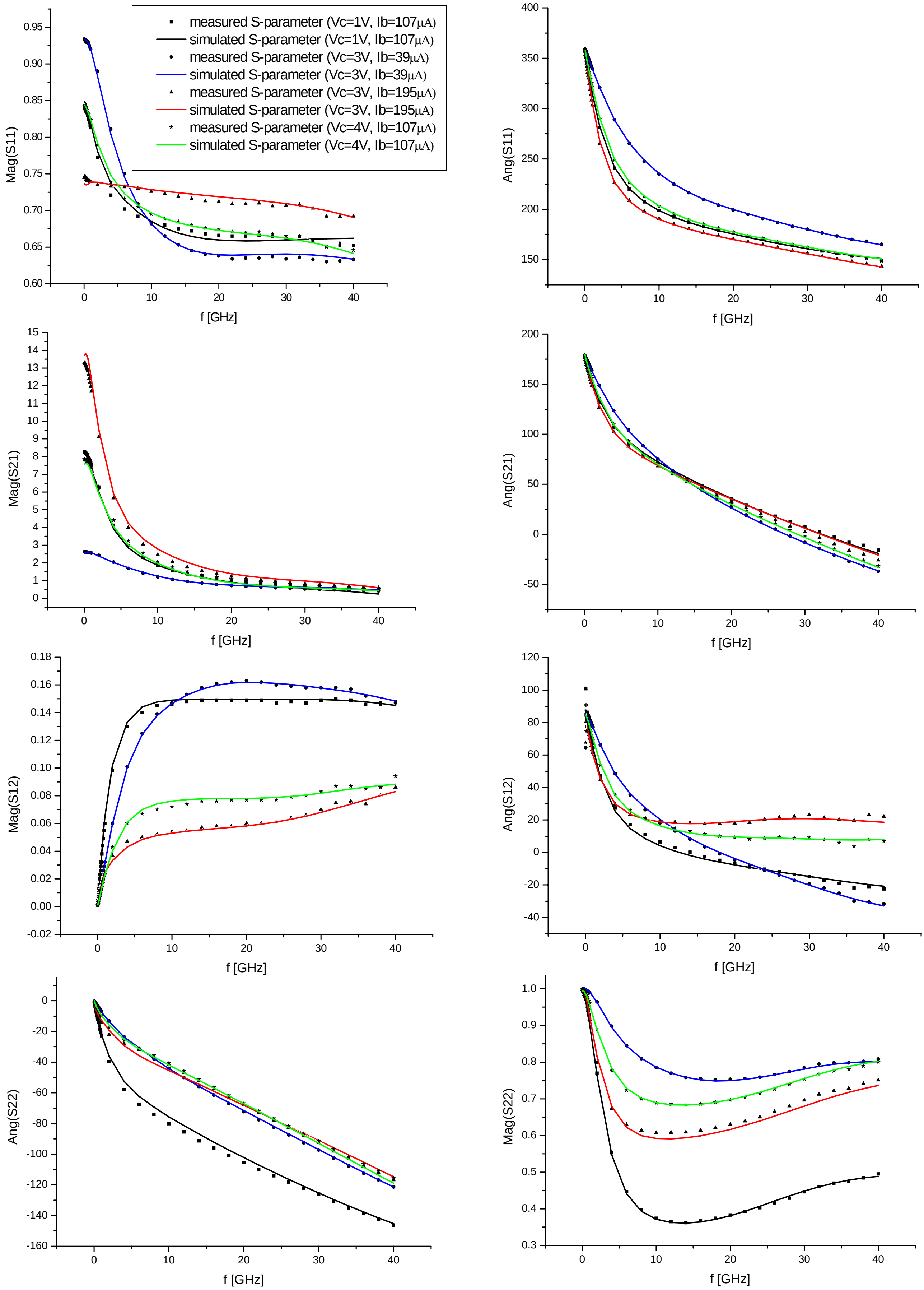

Figure 2. Results for *S* parameter characteristics obtaine by the neural model, compared to the experimental data