A Unified Neural Network for DC and RF Modeling of AlGaAs HBT's

Vera Marković, Aleksandar Stošić

Abstract – **The advantages of heterojunction bipolar transistors (HBTs) make them very promising for modern RF communication systems and there is a need for their valid description by means of a model. A procedure for HBT DC and RF modeling based on a unified neural network approach is presented in this paper. The proposed model is characterized by high accuracy and efficiency commonly requested for today's CAD techniques.**

Keywords – **HBT, neural networks, modeling**

I. Introduction

Due to the continuously increasing performance of digital wireless communication systems, the performances of active microwave devices have undergone a tremendous improvement in recent years as well. The range of modern microwave transistor available for the microwave wireless communication systems is wide and includes MESFETs, HEMTs, PHEMTs, HBTs, MOSFETs, etc. The choice of the RF transistors depends on the performance required for the selected wireless application as well as from the commercial accessibility, price, availability of CAD models and so on.

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

Due to the increasing application of HBT's in microwave circuits and having a need for efficient design of these circuits, a valid description of these devices by means of a model is required. A shift in the design of microwave components can be observed: in addition to the electrical characteristics, other issues such as reduced time to market, yield optimization, manufactured-oriented design, tolerance analysis, etc., are becoming increasingly important.

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 a standard, fast and enough accurate model for HBTs. In most case, the Gummel-Poon model is insufficient for today's bipolar transistors. A lot of DC models and RF models can be find in the literature. The advanced transistor models could characterize the transistor operation in a large bias and frequency range at the cost of more complicated extraction methods and measurement efforts due to a large number of unknowns of the transistor equivalent circuit. However, it is not convenient to perform statistical CAD which requires, for instance, hundreds of analysis, by using these approaches.

Last years, from the aspect of efficiency, accuracy and simplicity, neural network approach has been considered to be a good solution for microwave device modeling [5]. They can handle severe nonlinearities that are present in the majority of practical problems. They are especially useful in situations where a classical model-based or parametric approach to information processing is difficult to formulate.

Once developed 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 vectors not included in the training set, without additional computational efforts or new measurements.

In this paper, the application of neural network approach for modeling DC and RF performances of AlGaAs/GaAs HBTs is presented. In this way, an efficient prediction of transistor's characteristics over the wide frequency and bias condition ranges can be enabled.

II. Modeling of HBT's by using Neural Network Approach

Fig 1. shows an overall neural network configuration that provides DC and *S*-parameters of an HBT at the output for any frequency and bias point within the transistor's operating range, presented at the input.

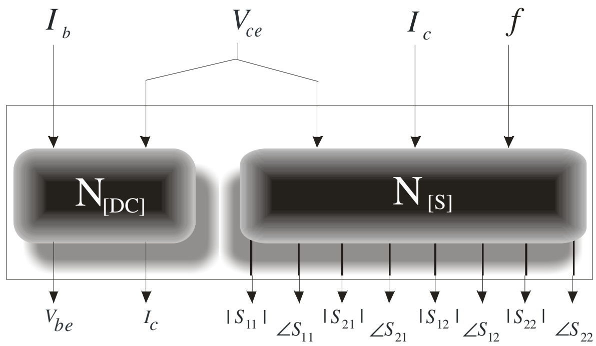

Fig 1. Neural network for DC and RF modeling of HBT's.

Neural network configuration presented in Fig. 1 is composed of two sub-networks, one for DC modeling, denoted by $N_{[DC]}$, and the other for *S*-parameter modeling, denoted by $N_{[S]}$. Both sub-networks are MLP (***M**ulti-**L**ayer **P**erceptron Network*)-type neural networks.

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Neural sub-network $N_{[DC]}$ provides DC collector current I_c and DC base-emitter voltage V_{be} for any DC collector-emitter voltage V_{ce} and DC base current I_b within the transistor's operating range presented at the input of neural model. With respect to that, there are two neurons in the input layer corresponding to V_{ce} and I_b, and two neurons in the output layer corresponding to V_{be} and I_c.

Therefore, the proposed neural model can predict two DC characteristics: 1) $I_c(V_{ce}, I_b)$ - DC collector current I_c in terms of DC collector-emitter voltage V_{ce} and DC base current I_b, and 2) $V_{be}(V_{ce}, I_b)$ - DC base-emitter voltages V_{be} in terms of DC collector-emitter voltage V_{ce} and DC base current I_b. The DC data needed for obtaining a training set for the first sub-network have been measured for AlGaAs HBT's with common emitter configuration.

The second neural sub-network denoted by $N_{[S]}$ enables an accurate prediction of magnitudes and angles of four *S*-parameters over the whole frequency range and for any DC collector-emitter voltages V_{ce} and DC collector current I_c within the operating bias range. Hence, there are three neurons in the input layer of the second sub-network $N_{[S]}$ corresponding to V_{ce}, I_c, and frequency *f*, and eight neurons in the output layer corresponding to the magnitudes and angles of *S*-parameters.

In both cases two hidden layers have been chosen because in this way slightly better have been obtained than with a structure containing only one hidden layer. The numbers of neurons in hidden layers have been selected on the basis of testing several networks with different numbers of hidden neurons.

The neural sub-networks have been trained using a back-propagation algorithm that is commonly considered as quite adequate for this purpose. In order to compare the accuracy of the model, the average test error (ATE [%]), the worst-case error (WCE [%]), and the *Pearson Product-Moment* correlation coefficient (r) between the measured and simulated data [5] 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.

The test procedure has been performed 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 of checking the generalization capability of developed neural networks.

The data for training and test sets that we used in modeling procedure had been obtained by the collaboration with a microwave laboratory at Northeastern University, Boston, USA, where HBT DC and *S*-parameter measurements were performed. The DC and *S*-parameter were directly measured on wafer AlGaAs HBT's denoted by HBT40020-002-8.

The measured data for V_{be} and I_c refer to collector-emitter voltages V_{ce} within -0.5V÷6V range and to base currents I_b of 50, 130, 210, 290 and 370 [μA]. The overall V_{ce} range was divided into two sub-ranges as follows: first sub-range (-0.5÷1)V with 0.05V step, and second sub-range (1÷6)V with 0.5V step. Therefore, the operating DC collector-emitter voltages V_{ce} range was covered with 41 discrete V_{ce} points and the operating DC base currents I_b range was covered with 5 discrete points. The V_{be} data and I_c data refer to 205 points and the total number of these DC data used in training and test procedure for the selected HBT transistor was 410. From this number, 328 data were used for the training and the rest of 82 data was used for a test set with the aim to check the generalization capability of the neural network.

Neural networks with a different number of hidden neurons varying between 2 and 10 neurons, have been trained. With the aim to additional improve the accuracy of ANN noise model triple successive training each neural network was performed. Therefore the effective number of trained neural networks was $3 \times 90 = 270$. The number of training epochs of each network was limited to a maximum of 180. The average time needed for the training process on a Pentium 4 with processor declared on 2500+ and 512MB RAM was 35 minutes. However, once trained, the network provides an instantaneous response for different input vectors.

The total number of *S*-parameters data used for training and test procedure for the selected HBT transistor was 5880. The data refer to the frequency range (0.05÷40) GHz. This frequency range was divided into four sub-ranges as follows: first sub-range (0.05÷0.5) GHz with 0.05 GHz step, second sub-range (0.5÷1) GHz with 0.1 GHz step, third sub-range (1÷10) with 1 GHz step, and fourth sub-range (10÷40) GHz with 2 GHz step. Therefore, operating frequency range was covered with 35 discrete frequency points. *S*-parameters have been measured for different combinations of DC collector-emitor voltages and base currents in the whole frequency range. DC collector-emitter bias had the fallowing values: 1V, 3V, 4V, and DC collector current had the following values [mA]: 0.5, 1.11, 2.03, 4.26, 9.01, 20.23, 29.99. Therefore, the measurements have been performed at 735 operating points and eight *S*-parameter data (magnitudes and angles) correspond to each point: $|S_{11}|$, $\angle S_{11}$, $|S_{12}|$, $\angle S_{12}$, $|S_{21}|$, $\angle S_{21}$, $|S_{22}|$, and $\angle S_{22}$. Training set was obtained by extracting 595 data points from the measurement data. Therefore the training set contained 4760 *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 this range to the range (0÷360)° has been applied.

By using these measured data, several neural networks with different number of hidden neurons (between 9 and 16) have been trained in the similar way as above.

In order to check the generalization capability of neural sub-network $N_{[S]}$, a test set is generated from the rest of data points containing 1120 *S*-parameters data. The bias points that have not been included in the training set had the following values:

1) $V_{ce} = 3V$, $I_c = 1.11mA$; 2) $V_{ce} = 1V$, $I_c = 4.26mA$;
3) $V_{ce} = 3V$, $I_c = 8.43mA$; 4) $V_{ce} = 4V$, $I_c = 4.09mA$

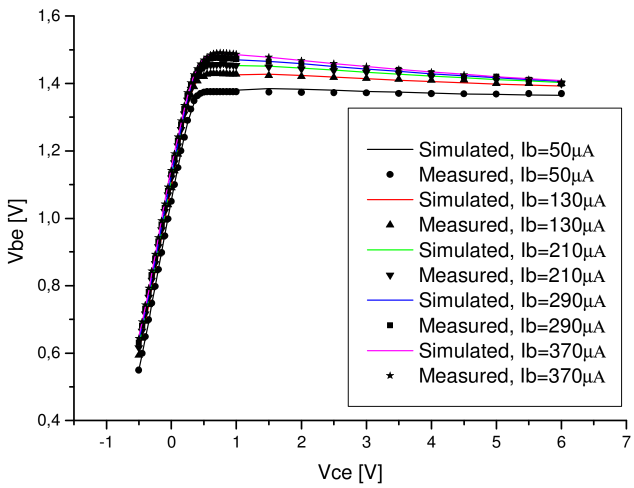

Fig. 2. The simulated (continual curve) and measured (symbols) DC characteristics $V_{be}(V_{ce}, I_b)$

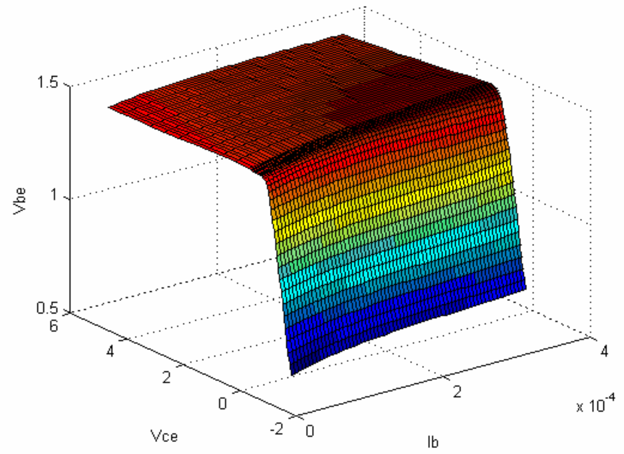

Fig. 4. Three-dimensional $V_{be}(V_{ce}, I_b)$ DC characteristics

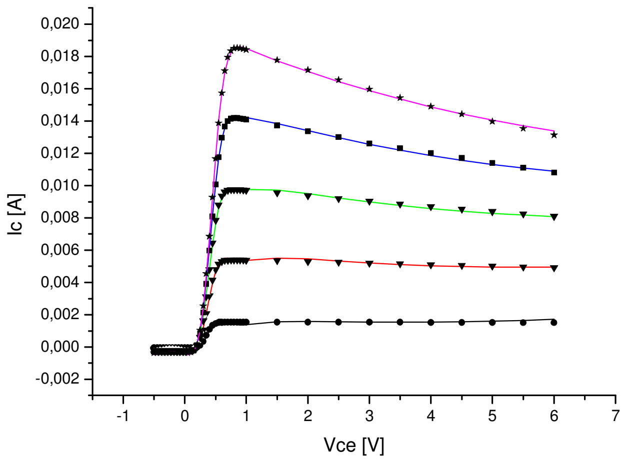

Fig. 3. The simulated (continual curve) and measured (symbols) DC characteristics $I_c(V_{ce}, I_b)$

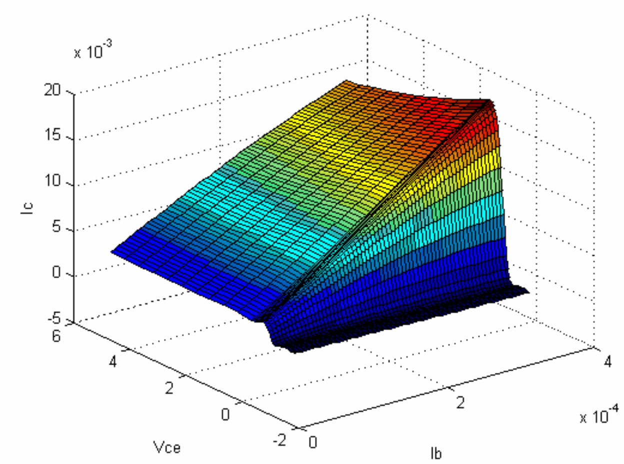

Fig. 5. Three-dimensional $I_c(V_{ce}, I_b)$ DC characteristics

III. Modeling Results

After the training process, neural models have been applied to get DC outputs as well as scattering parameter values for various input data different from the ones used for training. The results have been compared and on the basis of above-mentioned criteria, the best model has been selected. The best results give the first sub-network $N_{[DC]}$ marked by 1M4_4_9 and the second sub-network $N_{[S]}$ marked by 1M4_15_14. The number 1 denotes first of three successive training for the selected neural network. The number 4 shows that the neural network has four layers. Numbers 4 and 9 denote the number of neurons in the first and second hidden layer, respectively.

In Table 1, as an illustration of the accuracy of the selected model, test statistics for DC characteristics for training and test data is presented. It could be seen that the value of ATE for the training set data is less than 0,442%, and for the test set data is less than 0,602%. The value of WCE for the training set data is less than 1,660%, and for the test set data is less than 1,784%. The correlation coefficient *r*, in all cases, is

TABLE 1 Error statistics for DC characteristics

		ATE[%]:	WCE[%]:	r:
Training data	V_{be}	0.347	1.198	0.9999
	I_c	0.442	1.660	0.9998
Test data	V_{be}	0.476	1.197	0.9999
	I_c	0.602	1.784	0.9999

greater than 0.99. These results show that the selected neural sub-network $N_{[DC]}$ gives results of great accuracy and the excellent predictive ability.

The simulated DC characteristics obtained by the selected neural model, compared with measured data, are presented in following figures: DC base-emitter voltages V_{be} and collector currents I_c versus DC collector-emitter voltages V_{ce} at five discrete DC base currents I_b points are shown in Fig. 2 and Fig. 3, respectively. It is important to note that the DC base-emitter voltages V_{be} and collector currents I_c are simulated for $I_b = 290\mu A$, a value not included in the training set. Very

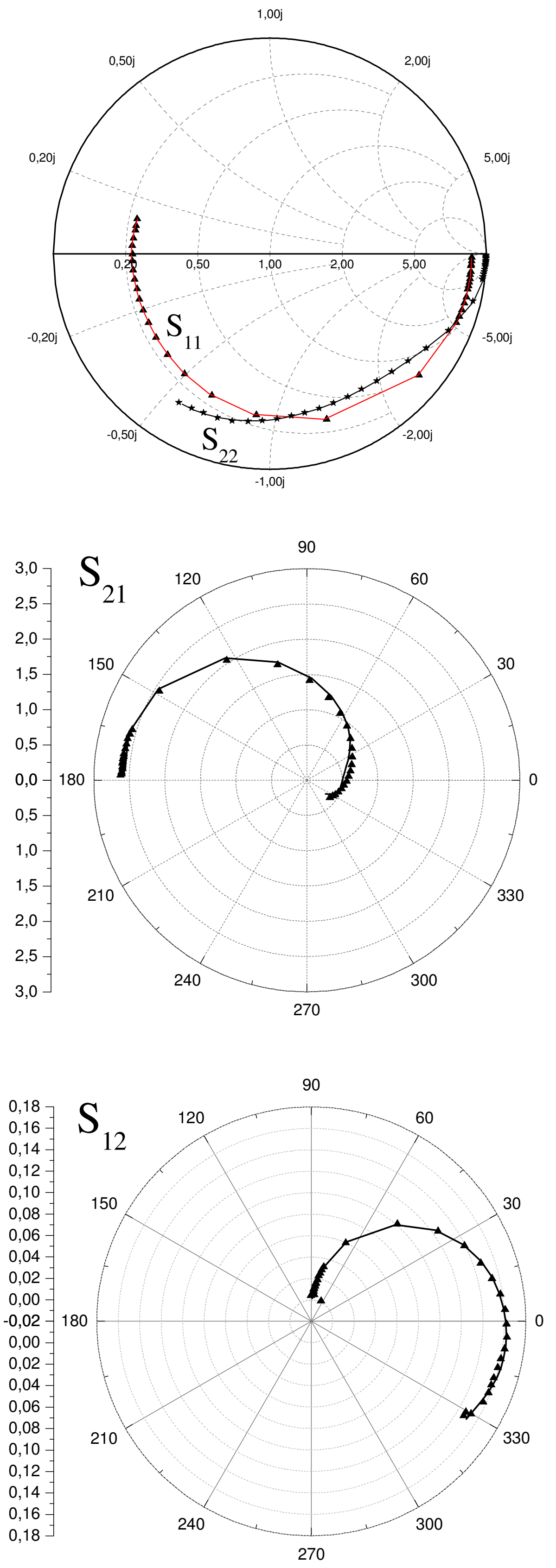

Fig. 6. The simulated (continual curve) and measured (symbols) *S*-parameters at the bias point $V = 3V$, $I = 1.11mA$

good agreement between simulated and measured characteristics can be observed in all cases, which means that the developed neural model has a good generalisation capability.

It is known that in some cases neural network over-learning could be happen. As a consequence, the prediction for the input values used for the training can be excellent (meaning very small ATE and WCE and correlation coefficient very close to one), but for some other inputs the network can give very bad and unexpected results. With the aim to checking the model validity additionally, neural network responses for practically continuous changes (small steps of change) of I_b and V_{ce}, have been generated and plotted. Figures 4 and 5 show the three-dimensional plots of DC base-emitter voltages V_{be} and DC collector currents I_c, respectively, as a function of continuous changes I_b and V_{ce}. The forms of three-dimensional surfaces confirm a very good prediction for the input values outside of the training set..

Fig. 6 shows the magnitudes and angles of *S*-parameters versus frequency, obtained by using the selected neural model, at a bias point not included in the training set. For the comparison purpose, measured data are shown in the same figure. It can be seen that the developed neural model can predict device *S*-parameters with a very good accuracy.

IV. CONCLUSION

A new, ANN-based unified approach can be used successfully for modeling the DC and *S*-parameters of HBTs. For developing a neural model only a number of measured data is needed. That gives an advantage to ANN approach in comparison with other modeling approaches, especially when the physical operating mechanisms of the device are too complex or not well known, which occurs often when some novel active devices for modern communication systems have to be considered. Developed neural models are characterized by high accuracy together with the efficiency and simplicity and therefore are convenient for CAD purposes.

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