ANNs in Bias-Dependent Modeling of S-parameters of Microwave FETs and HBTs

Zlatica Marinković, Aleksandar Stošić, Vera Marković, Olivera Pronić

Abstract – **The applications of artificial neural networks (ANNs) in bias-dependent modeling of S-parameters of microwave FETs and HBTs are considered in this paper. Besides a simple model based on an ANN that models S-parameter's dependence on the bias conditions and frequency, a model based on an ANN with additional prior knowledge at its inputs (PKI ANN) is introduced as well. S-parameters of the device that belongs to the same class as the modeled device are used as the prior knowledge. Further, a model of S-parameters for a class of devices made in the same technology and differ in the gate widths' values is proposed. All of the proposed models are illustrated by the appropriate modeling examples.**

Keywords – **Artificial neural network, MESFET, HEMT, HBT, S-parameters**

I. INTRODUCTION

Artificial neural networks (ANN) seem to be a good alternative to the conventional modeling in the field of microwaves. Unlike complex and time-consuming electromagnetic models, once developed neural models give responses almost instantaneously because response providing is based on performing basic mathematical operations and calculating elementary mathematic functions (such as an exponential or hyperbolic tangent function). ANNs have the capability of approximating any nonlinear function and the ability to learn from experimental data. Therefore, it is possible to develop neural model from source-response data points without knowledge about the physical characteristics of the problem to be solved.

The most important feature of neural models is their generalization capability, i.e. the capability of providing the correct response even for the input values not used during the ANN training process. In that way, the developed models can be used for a reliable prediction over a wide range of input parameters.

The ANNs have been applied to a wide range of modeling problems in the in the area of microwaves, [1]-[12]. There are ANN applications, either to passive devices, to active devices, or to whole systems.

This paper deals with application of ANN to the modeling of small-signal scattering parameters (S-parameters) of microwave transistors. The microwave transistors are the key parts of active microwave circuits. The most frequently used microwave transistors are FETs (*Field-Effect Transistors*) and HBTs (*Heterojunction Bipolar transistors*). Almost all of the standard FET transistors, like MESFET (*MEtal Semiconductor FET*) and HEMT (*High Electron Mobility Transistor*), have a very low-noise level, and therefore they are suitable to be applied to the low-noise microwave active circuits. Heterojunction Bipolar Transistors (HBTs) have become very promising devices for different applications at the microwave and millimeter-wave frequencies. HBT technology is considered as very convenient for RF front-end circuits in next-generation wireless communications.

When operating under small-signal conditions, the microwave transistors can be characterized by the scattering parameters. Processes of design, optimization and analyses of the microwave active circuits require accurate and reliable models of S-parameters of the microwave transistors. Most of the existing small-signal models are based on an equivalent circuit representation of the device. The equivalent circuit elements are extracted usually from the measured S-parameters within a microwave circuit simulator.

Although the device S-parameters are bias-dependent, most of the small-signal models are valid for only one bias. For any other bias, it is necessary to extract the equivalent circuit parameters from the measured S-parameters for that bias. That procedure can be very time-consuming in the case when models for various bias conditions are required.

In this paper, bias-dependent models of the S-parameters are proposed. It is started from a model based on an ANN that models S-parameters dependence on bias conditions and frequency. Similar models are proposed in [3] and [4] for FETs and in [5] and [6] for HBTs. Once developed, this model enables prediction of S-parameters in the whole device operating range without additional optimizations or additional measurements.

Further, a prior knowledge input (PKI) model is introduced. The main aim of this model is to use prior knowledge about S-parameters as additional inputs into the ANN model in order to increase the modeling accuracy. In the proposed case, those are S-parameters of the device that belongs to the same class as the modeled device.

An S-parameters' model of different-gate-width microwave FET transistors is considered as well. It is an extension of the basic model - its inputs are not only bias conditions and frequency, but also device gate-width. Therefore, this model is valid for a whole class of devices made in the same technology.

Validity of the proposed models is verifie`d by the appropriate modeling examples.

II. ARTIFICIAL NEURAL NETWORKS

A standard multilayer perceptron (MLP) artificial neural network (ANN) is shown in Fig.1, [1]. This network consists of an input layer (layer 0), an output layer (layer N_L) as well as several hidden layers.

Authors are with the Faculty of Electronic Engineering, Aleksandra Medvedeva 14, 18000 Niš, Serbia and Montenegro
E-mail: [zlatica, stosha, vera, oljap]@elfak.ni.ac.yu

Input vectors are presented to the input layer and fed through the network that then yields the output vector. The l-th layer output is:

$$\mathbf{Y}_l = F(\mathbf{W}_l \mathbf{Y}_{l-1} + \mathbf{B}_l) \quad (1)$$

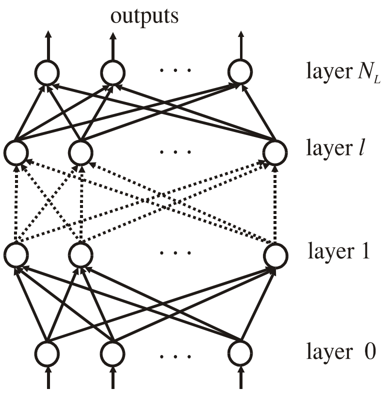


Fig.1. *MLP neural network*

where $\mathbf{Y}_l$ and $\mathbf{Y}_{l-1}$ are outputs of l-th and (l-1)-th layer, respectively, $\mathbf{W}_l$ is a weight matrix between *(l-1)*-th and l-th layer and $\mathbf{B}_l$ is a bias matrix between *(l-1)*-th and l-th layer. Function F is an activation function of each neuron and, in our case, is linear for input and output layer and sigmoid for hidden layers:

$$F(u) = 1/(1+e^{-u}) \quad (2)$$

The neural network learns relationship among sets of input-output data (training sets) that are characteristics of the component under consideration. First, input vectors are presented to the input neurons and output vectors are computed. These output vectors are then compared with desired values and errors are computed. Error derivatives are then calculated and summed up for each weight and bias until whole training set has been presented to the network. These error derivatives are then used to update the weights and biases for neurons in the model. The training process proceeds until errors are lower than the prescribed values or until the maximum number of epochs (epoch - the whole training set processing) is reached. Once trained, the network provides fast response for different input vectors, even for those not included in the training set, without additional optimizations.

In order to quantify accuracy of the ANN model, average test error (ATE [%]), worst-case error (WCE [%]), and correlation coefficient, *r,* between the referent and the modeled data are calculated, [1].

The Pearson Product-Moment correlation coefficient r is defined by:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \quad (3)$$

where x_i is referent value, y_i is the neural network computed value, $\bar{x}$ is the referent sample mean, and $\bar{y}$ is the neural network sample mean. The correlation coefficient indicates how well the modeled values match the referent ones. A correlation coefficient near one indicates an excellent predictive ability, while a coefficient near zero indicates poor predictive ability.

III. MICROWAVE TRANSISTOR S-PARAMETERS

Microwave FETs and HBTs operating under small-signal conditions can be characterized by the scattering parameters (S-parameters) which relates the voltage waves incident on the ports to those reflected from the ports (Fig.2).

The scattering matrix, or [S] matrix, is defined in relation to these incident and reflected voltage waves as, [13]:

$$\begin{bmatrix} V_1^- \\ V_2^- \end{bmatrix} = \begin{bmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{bmatrix} \begin{bmatrix} V_1^+ \\ V_2^+ \end{bmatrix} \quad (3)$$

or in matrix notation

$$[V^-] = [S][V^+]. \quad (4)$$

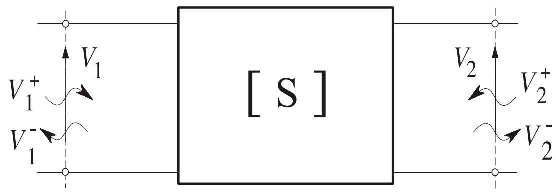


Fig.2. *Incident and reflected waves in a two-port network*

An element of the [S] matrix can be determined as

$$S_{ij} = \frac{V_i^-}{V_j^+}\bigg|_{V_k^+=0,\text{za } k\neq j} \quad (5)$$

S_{ii} is the reflection coefficient seen looking into the port i when all other ports are terminated in load matches. S_{ij} is the transmission coefficient from port j to port i when all ports are terminated in matched loads.

The S-parameters of microwave transistors are frequency-, temperature- and bias-dependent.

IV. BIAS-DEPENDENT ANN MODEL

ANNs can be applied for modeling bias- and frequency-dependences of microwave transistor S-parameters. The model considered here consists of an MLP ANN trained to predict transistor S-parameters for given bias voltage, bias current and frequency at its inputs, Fig. 3. Therefore, the network has three input neurons corresponding to

- bias voltage,
- bias current and
- frequency f .

In the case of FET modeling, the bias voltage is dc drain-to-source voltage, V_{ds} , and the bias current is dc drain-to-source current, I_{ds} . In the case of HBT modeling, the bias voltage is dc collector voltage, V_c , and the bias current is dc base current, I_b .

The output layer consists of eight neurons corresponding to magnitudes and angles of the scattering parameters.

Number of the hidden layers can be one or two. The network is trained using S- parameters' data referring to certain number of bias points in the operating frequency range. Neural networks with different number of hidden neurons are trained, tested and after their comparison, the network giving the best testing results is chosen to be the bias-dependent model of S-parameters of the modeled device.

Once the model is developed, its structure remains unchanged. The S-parameters are obtained by calculating the ANN response to the given bias conditions and frequency. It should be emphasized that measured values of the device S-parameters are required only for the model development.

A. Modeling Examples

The above-proposed approach was applied to Hewlett Packard pHEMT device ATF35143 and to AlGaAs HBT40020-002-8 HBT device.

The data used for the model development for pHEMT was taken from the device manufacturer web-site, [14]. They refer to 9 bias points (V_{ds}, I_{ds}) in (0.5-18) GHz frequency range (23 frequency points per one bias point). The data referring to 8 bias points were used as the ANN training data and the data for the remaining bias points were used as validation test data.

In the case of HBT, the used S-parameter data were obtained by measurement in the microwave laboratory of the Northeastern University, Boston, USA. The data refer to 21 bias points (V_c, I_b) in (0.05-40) GHz frequency range. Per each bias points there were 35 frequency points. The data referring to 17 bias points were used as the ANN training data and the data for the 4 remaining bias points were used as validation test data.

The angles of S-parameters were expressed in one of (0°÷360°) or (-180°÷180°) ranges. The criterion for the range selection, for the angle of each S-parameter, is the angle frequency dependence without sharp changes. This is elaborated in details in the next sub-section.

Training, testing and evaluation procedures of these two devices were done separately. For both of the devices, ANNs with three input, eight output and different number of hidden neurons were trained. The prediction of S-parameters by all of the obtained ANNs was tested for the corresponding training and test sets. After comparison of the test results, ANNs giving the best results were chosen for each device.

The best-obtained ANN for pHEMT device is an ANN that has two hidden layers with 10 neurons in each. For HBT device, the best-obtained ANN is the one that has 16 neurons in the first and 15 neurons in the second hidden layer, viewing from the input to the output layer.

In Table I, there are statistical results of the prediction of pHEMT S-parameters obtained by the selected ANN for bias points used for the training. Very low values of the ATE and WCE and correlation coefficients very close to one show that the network learnt training data very well. Prediction of the S-parameters for the remaining bias point is shown in Fig. 4. Although this point was not presented to the ANN during the training process, the ANN gives S-parameters (solid line with open dots at the frequencies corresponding to the reference data) that are very close to the reference ones (full dots).

In Table II and III, there are statistical results of prediction of HBT S-parameters obtained by the corresponding ANN for bias points from the training set and for those outside of the training set, respectively. It can be seen, from the both Tables, that the values of ATE and WCE are very low, and correlation coefficients are very close to one, with an exception of prediction of the angle of S_{12} parameter, where the WCE is significantly higher then the other WCE values. But since the ATE values and correlation coefficients (for the both training and test data) for this parameter, are still acceptable, it can be concluded that prediction of the angle of S_{12} parameter is satisfying as well. Therefore the results shown in the Tables indicate that the obtained ANN is able not only to predict the training data very well but also to predict the test data, that differ from ones from the training set, with quite good accuracy. The generalization ability can be confirmed from the Fig. 5, where the S-parameters for two bias points outside of training set are given. The ANN obtained values (lines) match very well with the measured ones (symbols).

B. Recommendations

Sharp change in the frequency dependency of the angles of some S-parameter can affect modeling of that parameter making it worse. The following example can be used as explanation of the above stated. Suppose that the dependence of the of S_{22} parameter on frequency is being modeled and that the frequency dependence of its angle has a sharp change from -180° to 180°, as it is depicted in Fig. 6. Furthermore, suppose that magnitude of S_{22} parameter is modeled correctly and consider only modeling of the S_{22} angle. The available measured values, represented by full dots, are used for the training process of an ANN, which will be used as a model of this frequency dependence. Since, there are not enough training data in the vicinity of the sharp change, which is often the case, the trained ANN is most likely not to achieve accurate modeling in this region. The ANN response is represented with dotted line. The ANN obtained values for the frequencies corresponding to the reference values are denoted by triangles. It is obvious that satisfying modeling has not been achieved only in the region of the sharp change, moreover, it is very poor. Due to the poor modeling in this region, there is a "circle" in the modeled S_{22} plot in polar diagram, which does not exist in the actual S_{22} plot, Fig. 7.

Then, the angle of S_{22} parameter is expressed in the range (0°÷360°), and another ANN is trained by using the new data. Since the frequency dependence is smooth now, the trained ANN is able to model it with a very good accuracy, as it is shown in Figs. 7 and 8. The ANN obtained values are represented by solid lines. Open circles represent the ANN obtained values for the frequencies corresponding to the reference values.

Therefore, for each S-parameter, it is recommended to express training and test values of its angle in one of (0°÷360°) or (-180°÷180°) ranges where there is no sharp change in the frequency characteristic. In that way, modeling accuracy can be significantly increased.

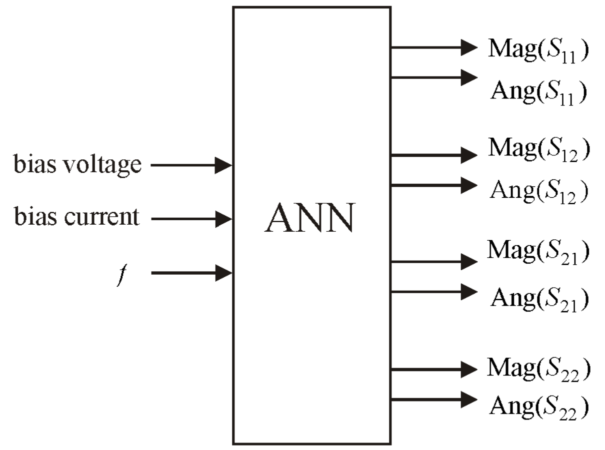


Fig.3. *Bias-dependent ANN model*

Table I. Testing results for the bias points used in the training process (ATF35143 pHEMT)

	ATE[%]	WCE[%]	*r*
$\lvert S_{11}\rvert$	0.866	2.076	0.99981
$Ang(S_{11})$	0.490	1.314	0.99993
$\lvert S_{21}\rvert$	0.353	0.739	0.99994
$Ang(S_{21})$	0.530	1.155	0.99989
$\lvert S_{12}\rvert$	1.333	1.866	0.99994
$Ang(S_{12})$	0.394	1.401	0.99991
$\lvert S_{22}\rvert$	1.163	2.964	0.99954
$Ang(S_{22})$	0.729	2.231	0.99968

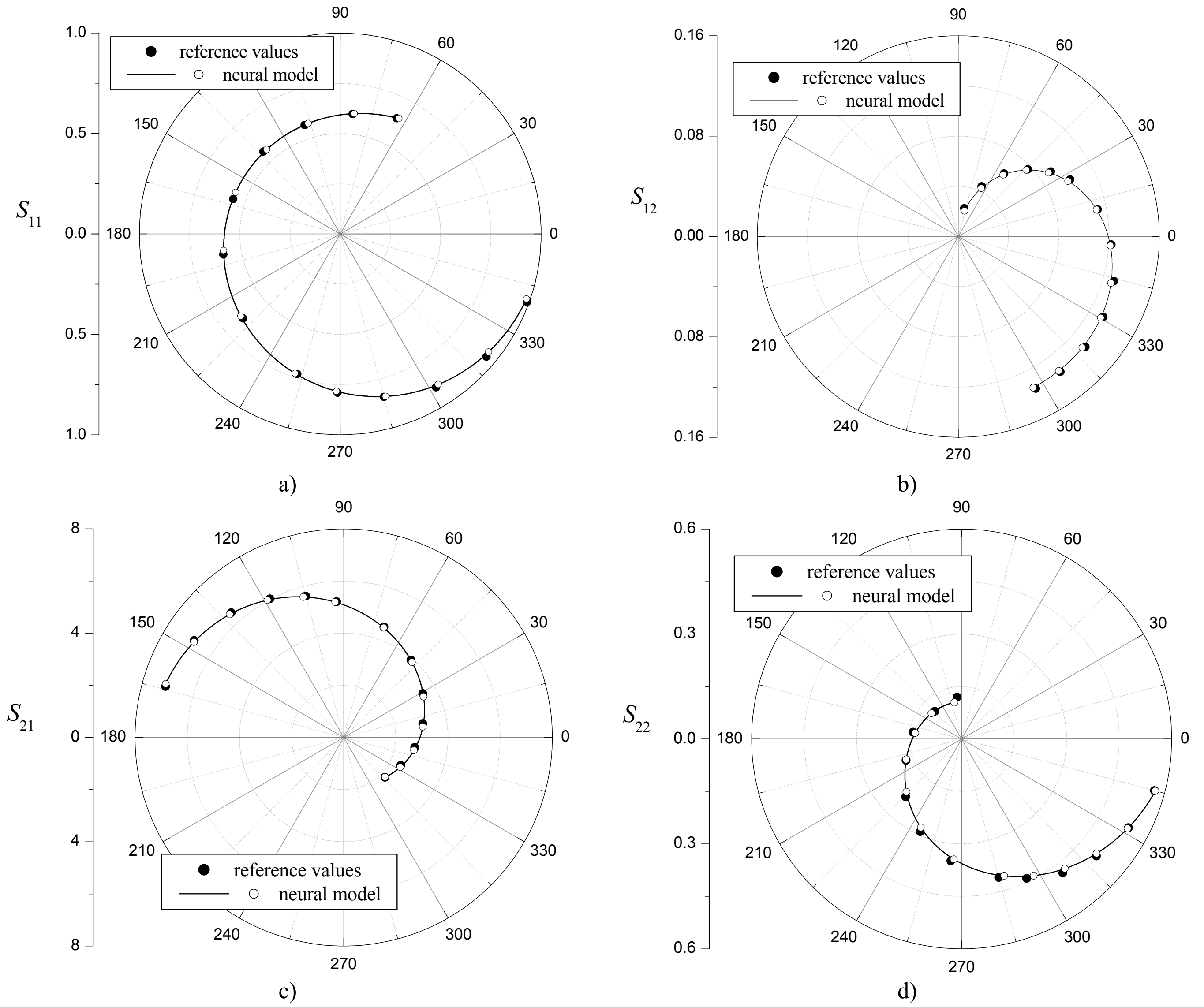


Fig. 4. Scattering parameters for a bias point not used for the training process (ATF35143 pHEMT)
a)S_{11} b) S_{12} c) S_{21} d) S_{22}

Table II. Testing results for the bias points used in the training process (HBT40020-002-8)

	ATE[%]	WCE[%]	r
$\lvert S_{11}\rvert$	0.311	1.805	0.99975
$Ang(S_{11})$	0.231	4.382	0.99994
$\lvert S_{12}\rvert$	0.315	1.736	0.99982
$Ang(S_{12})$	0.516	12.844	0.99857
$\lvert S_{21}\rvert$	0.220	1.621	0.99992
$Ang(S_{21})$	0.260	1.362	0.99994
$\lvert S_{22}\rvert$	0.258	1.732	0.99993
$Ang(S_{22})$	0.221	1.550	0.99992

Table III. Testing results for the bias points not used in the training process (HBT40020-002-8)

	ATE[%]	WCE[%]	r
$\lvert S_{11}\rvert$	1.378	5.321	0.99838
$Ang(S_{11})$	0.298	1.354	0.99995
$\lvert S_{12}\rvert$	0.965	3.508	0.99939
$Ang(S_{12})$	1.271	15.718	0.99603
$\lvert S_{21}\rvert$	1.375	5.500	0.99863
$Ang(S_{21})$	0.477	2.555	0.99982
$\lvert S_{22}\rvert$	0.872	2.906	0.99941
$Ang(S_{22})$	0.784	3.837	0.99932

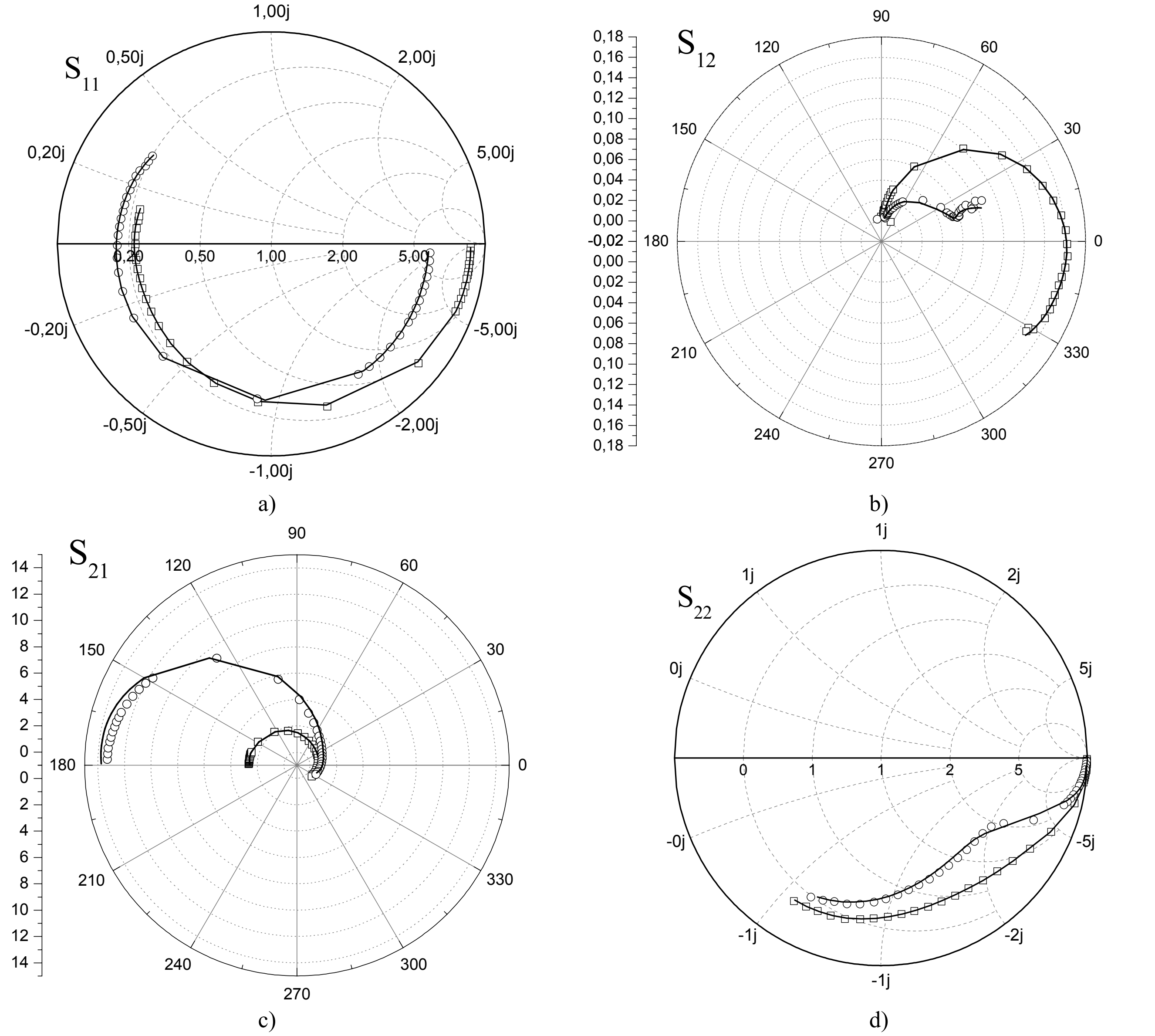


Fig. 5. Scattering parameters for bias points not used for the training process (HBT40020-002-8)
a)S_{11} b) S_{12} c) S_{21} d) S_{22}

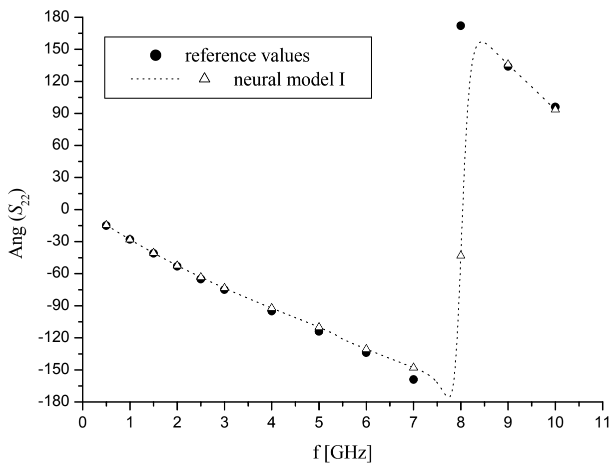


Fig. 6. S_{22} parameter angle expressed in the (-180° - 180°) range

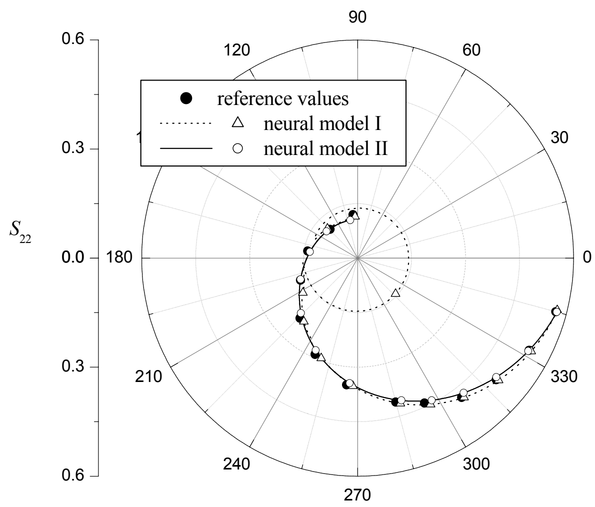


Fig. 7. S_{22} parameter – polar plot

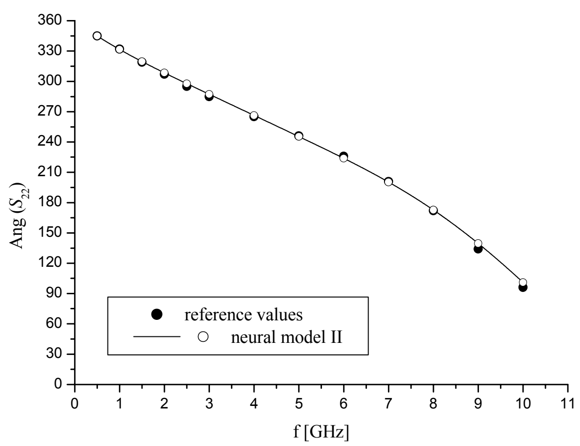


Fig. 8. S_{22} parameter angle expressed in the (0°-360°) range

V. Bias-dependent PKI ANN model

Introducing prior knowledge about the problem being modeled increases the modeling accuracy, [1]. ANNs with prior knowledge at its inputs are known as *prior knowledge input* (PKI) ANNs. Here, a PKI ANN model as a bias-dependent model of S-parameters of microwave transistor is proposed. In Fig. 9 there is a PKI ANN model of microwave FETs. A corresponding model of HBTs can be built using the same approach. The inputs of a PKI ANN model (ANN Device1 in Fig. 9) are not only bias conditions and frequency (as in the basic ANN model) but also S-parameters corresponding to these input values. We propose that the approximate values are obtained by a basic ANN model of S-parameters (ANN Device 0 in Fig. 9) developed earlier for a device from the same class as the modeled device.

In this way, for the same training set, the model accuracy increases, as it will be presented in the following example.

A. Modeling Example

The proposed PKI ANN model was developed for ATF34143 pHEMT device (Hewlett Packard). The measured S-parameter data for this device available on the manufacturer web-site, [14] refer only to four bias points (V_{ds}, I_{ds}) in (0.5-18) GHz frequency range (23 frequency points per one bias point). Although, it is possible to train an ANN to learn these data accurately, it is not possible to achieve any acceptable generalization. Therefore, the PKI ANN model was developed. The prior knowledge input values were those obtained by the basic ANN model (ANN0) developed for ATF35143 pHEMT device, which belongs to the same class as ATF34143 and differs from it only in the gate width value. Since the ATF35143 model development is described in the modeling example within Section IV, here the ANN1 development is described.

The available data were divided in two subsets: the data referring to three bias points were used as the ANN (ANN1) training data and the data for the remaining bias point were used as the validation test data. The angles of S-parameters were expressed in one of (0°÷360°) or (-180°÷180°) ranges. The criterion for the range selection, for the angle of each S-parameter, is the angle frequency dependence without sharp changes, as it is elaborated in details in the sub-section Recommendations within Section IV.

ANNs with 11 input, 8 output and different number of hidden neurons were trained. The prediction of S-parameters by all of the obtained ANNs was tested for the corresponding training and test sets. After comparison of the test results, the ANN with two hidden layers, with 10 neurons in each hidden layer, was chosen as the best model.

In Table V there are statistical results of prediction of the S-parameters by the developed PKI ANN model for bias points used for the training. Low values of the ATE and WCE and correlation coefficients very close to one indicate that the network learnt the training data very well. Prediction of the S-parameters for the remaining bias point is shown in Fig. 12. The ANN obtained S-parameters are represented by lines and the reference (measured) values are represented by symbols.

Although, the ANN obtained values are not as close to the reference ones as it is case of ATF35143 device (Fig. 4), the generalization of this model can still be considered as acceptable.

VI. BIAS-DEPENDENT ANN MODEL FOR A CLASS OF FETS

The FET model proposed in Section IV is valid for the modeled device only. In order to extend its validity to a class of FET transistors, the transistor gate width, W , is proposed to be an additional input into the neural model. Therefore, the model proposed here (Fig. 11) is an MLP neural network with four neurons in the input layer corresponding to:

- gate width W ,
- dc drain-to-source voltage V_{ds} ,
- dc drain-to-source current I_{ds} and
- frequency f .

The output layer consists of eight neurons corresponding to magnitudes and angles of scattering parameters.

Number of the hidden layers can be one or two. The network is trained using S- parameters' data referring to several devices of different gate widths that are made in the same technology. Per each device it is necessary to acquire data for certain number of bias points in the operating frequency range. Generally, neural networks with different number of hidden neurons are trained, tested and after their comparison, the network with the best testing results is chosen to be the bias dependent neural noise model for the class of the modeled transistors.

A. Modeling Example

In this Section, some numerical modeling results are given. Three *Hewlett Packard's* pHEMT devices, ATF3x143 series, were modeled:

- ATF35143 (gate width 400μm),
- ATF34143 (gate width 800μm) and
- ATF33143 (gate width 1600μm).

The S- parameters used as the training data were taken from manufacturer WEB site [14]. These data refer to certain number of bias points. The S-parameters are available in (0.5-18) GHz frequency range per each bias point. The available set of the bias points was divided in two subsets, one used for the training of the neural networks (training set) and the other, smaller one, used for the evaluation of the network generalization capabilities (test set).

Neural networks with four inputs, eight outputs and different number of hidden neurons were trained using the same training set. All of the trained networks were tested on the training set and on the test set. The best results for the S-parameters modeling, for both - training and test sets, were obtained by a network with seven neurons in the first and four neurons in the second hidden layer.

Further, in Table IV there are statistic data for the bias points from the training set. It can be seen that ATE is lower than 1.9% and WCE is lower than 8.2%, showing that the ANN learnt training data very well. Considering these results and values of correlation coefficient r that are very close to one, it is obviously that very good modeling has been achieved.

As a further illustration, in Fig. 12, there are frequency dependencies of *S*- parameters for two devices referring to bias points not used in the training process. The ANN outputs are denoted by solid line and reference (measured) data by symbols. From the fact that the predicted values match very well to the referent ones, it can be confirmed that quite a good generalization has been achieved.

VII. CONCLUSION

ANN applications in bias-dependent S-parameter modeling of microwave FETs and HBTs are proposed in this paper. It is started from a model consisting of a single ANN that models S-parameters dependence on bias conditions (bias current and bias voltage) and frequency. The proposed ANN models are able to efficiently predict the S-parameters of a microwave FET/HBT for any given bias and frequency point from the device operating range with good accuracy, either for those used for the network training or for those presented to the network for the first time. Once the model is developed, its structure remains unchanged. Moreover, the measured data are required only for the model training procedure.

Further, a PKI model, as an extension of the above-mentioned basic ANN model is introduced. The PKI ANN model includes prior knowledge as the additional ANN inputs, which can help ANN to extract input-output dependence. S-parameters of the device belonging to the same class as the modeled device are used as a prior knowledge. In that way, in the case when there are no enough training data, it is possible to achieve sufficiently good generalization.

Both of the models, basic and PKI ones, are valid only for the modeled device type. In order to extend model to a whole class of devices, in the case of FET devices, the device gate width is introduced as an additional ANN input. The ANNs are trained using measured values of S-parameters for several different gate width devices produced in the same technology.

All of the proposed models can be easily implemented into standard microwave simulators. For this purpose, a set of mathematical expressions describing the selected ANN can be generated and implemented within the corresponding block of a simulator, which deals with variables and equations. In that way a bias-dependent user-defined library element for microwave transistor, i.e. for class of microwave transistors, can be created.

ACKNOWLEDGEMENTS

Authors would like to thank Prof. Sheila Prasad, Northeastern University, Boston, USA, for providing the experimental data used in this work.

This work was supported by Ministry of Science and Environmental Protection of Republic of Serbia, under the project 1351.

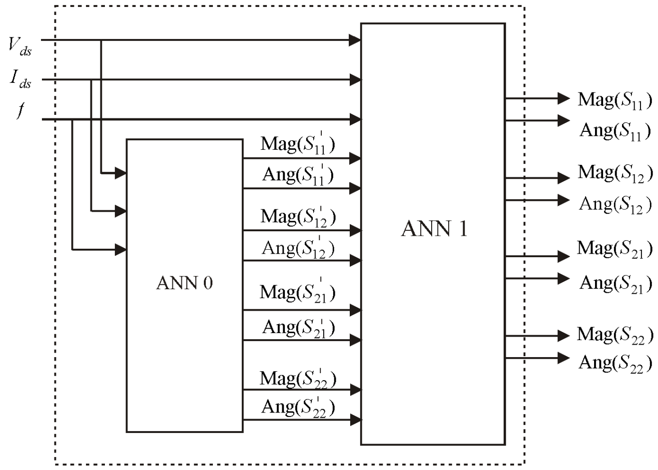


Fig.9. *Bias-dependent PKI ANN model of FETs*

Table IV. Testing results for the bias points used in the training process (ATF34143 pHEMT)

	ATE[%]	WCE[%]	r
$\lvert S_{11}\rvert$	1.899	5.874	0.99646
$Ang(S_{11})$	0.811	2.943	0.99968
$\lvert S_{21}\rvert$	1.546	5.077	0.99796
$Ang(S_{21})$	0.741	2.495	0.99969
$\lvert S_{12}\rvert$	1.228	6.717	0.99864
$Ang(S_{12})$	0.708	2.772	0.99979
$\lvert S_{22}\rvert$	1.565	6.311	0.99862
$Ang(S_{22})$	0.662	4.038	0.99963

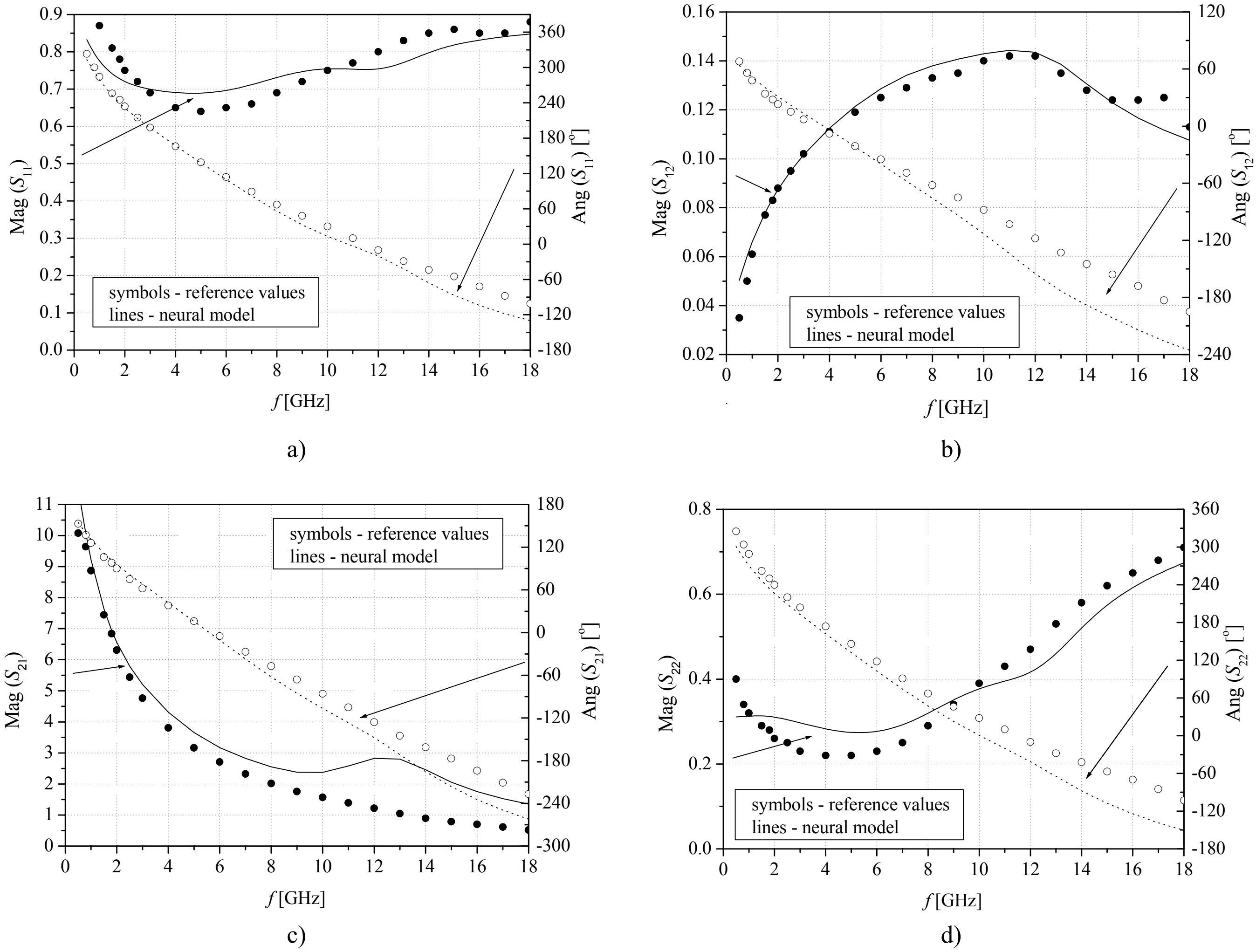


Fig. 10. Scattering parameters for bias points not used for the training process (ATF34143 pHEMT)
a)S_{11} b) S_{12} c) S_{21} d) S_{22}

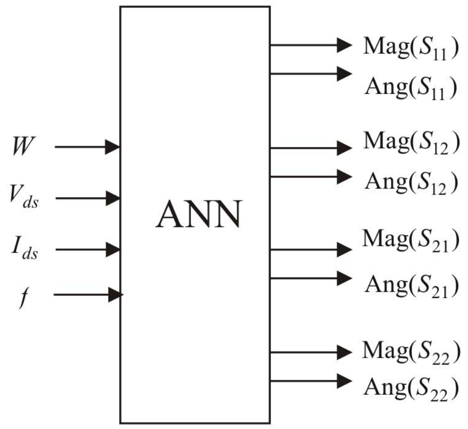
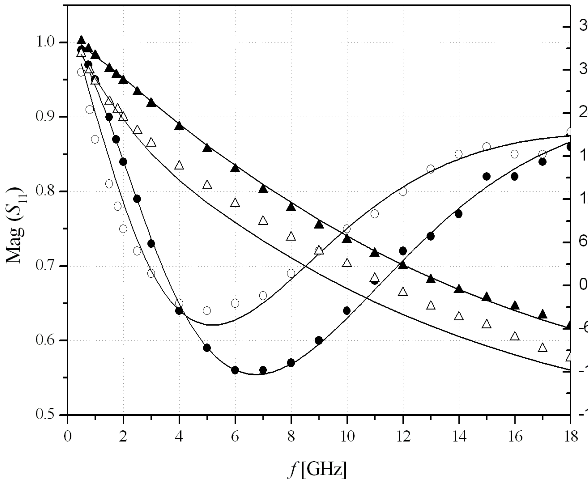


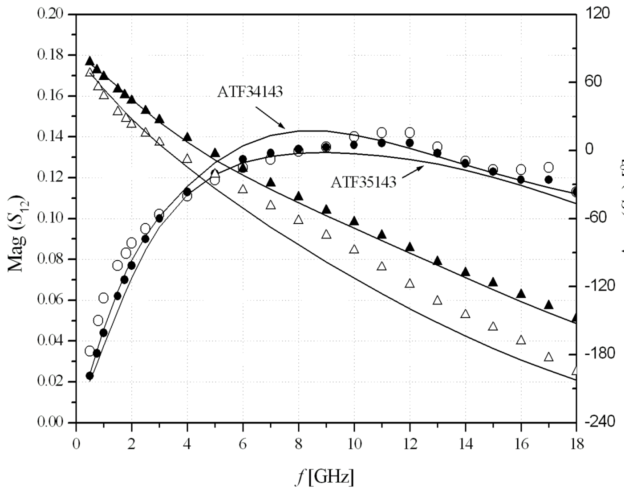
Fig.11. *Bias-dependent ANN model for a class of microwave FETs*

Table IV. Testing results for the bias points used in the training process

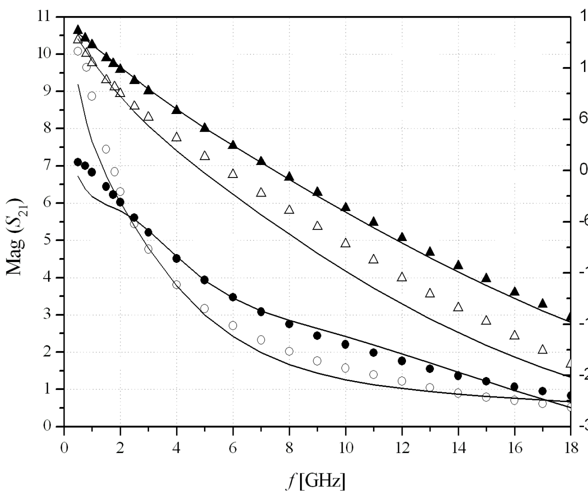
	ATE[%]	WCE[%]	r
$\lvert S_{11}\rvert$	1.813	7.032	0.99628
$Ang(S_{11})$	1.261	4.673	0.99859
$\lvert S_{21}\rvert$	1.154	7.079	0.99708
$Ang(S_{21})$	0.956	3.028	0.99912
$\lvert S_{12}\rvert$	1.954	6.869	0.99526
$Ang(S_{12})$	0.937	5.565	0.99891
$\lvert S_{22}\rvert$	1.457	8.165	0.99728
$Ang(S_{22})$	1.741	7.759	0.99699



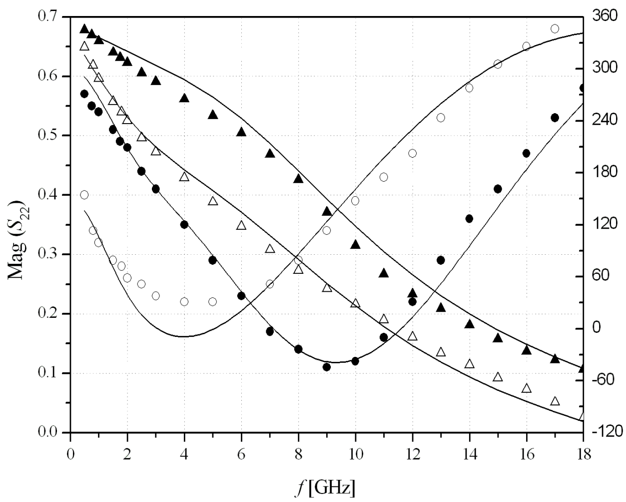
a)



b)



c)



d)

Fig. 12. Magnitudes (circles) and angles (triangles) of scattering parameters for bias points not used for the training process (black symbols – ATF35143 (2V, 15mA) ; white symbols - ATF34143 (3V, 20mA); solid lines – neural model output)
a)S_{11} b) S_{12} c) S_{21} d) S_{22}

REFERENCES

[1] Q. J. Zhang, K. C. Gupta, *Neural Networks for RF and Microwave Design,* Artech House, 2000.

[2] P. M. Watson, K. C. Gupta, “EM-ANN Models for Microstrip Vias and Intreconnects in Dataset Circuits”, *IEEE Trans., Microwave Theory Tech.,* Vol. 44, No-12, 1996, pp. 2495-2503.

[3] F.Gunes, H.Torpi, F.Gurgen, "Multidimensional signal-noise neural network model", *Circuits, Devices and Systems, IEE Proceedings,* Vol.145, Iss.2, Apr 1998, pp. 111-117.

[4] P.M. Watson, M. Weatherspoon, L. Dunleavy, G.L. Creech, “Accurate and Efficient Small-Signal Modelling of Active Devices Using Artificial Neural Networks”, *GAAS IC Symp.Technical Digest*, 1998, pp 95-98.

[5] V. K. Devbahaktuni, C. Xi, and Q. J. Zhang, "A neural network approach to the modeling of heterojunction bipolar transistors from *S*-parameter data", *Proc. of 28th European Microwave Conf.*, Amsterdam, pp. 306-311, Oct. 1998.

[6] M. Vai, S. Prasad, Neural networks in microwave circuit design – beyond black box models, *Int. J. RF and Microwave Computer-Aided Eng.*, Special issue on Applications of Artificial Neural networks to RF and Microwave Design, 1999, pp. 187-197.

[7] F. Giannini, G. Leuzzi, G. Orengo, M. Albertini, “Artificial neural network approach for MMIC passive and active device characterization” *Proc. of Gallium Arsenide applications symposium - GAAS 2000*, 2000, Paris.

[8] D. Schreurs, S. Vandenberghe, H. Taher, B. Nauwelaers, “ANN Model For SiGe HBTs Constructed From Time-Domain Large-Signal Measurements” *Proc. of Gallium Arsenide applications symposium - GAAS 2002,* 2002, Milano.

[9] Z.Marinković, V.Marković, “Prediction of HEMT's Scattering and Noise Parameters Using Neural Networks”, *Microwave Review*, Vol. 8, No.1, 2002, pp. 28-31

[10] K. Munshi, P. Vempada, S. Prasad, E. Sonmez, H. Schumacher, "Small signal and large signal modeling of HBT's using neural networks", *Proceedings of the 6th International Conference on Telecommunications in Modern Satellite, Cable and Broadcasting Services*, *TELSIKS 2003*, Niš, Serbia and Montenegro, 2003, Vol 2, pp: 565- 568

[11] V.Marković, Z.Marinković, "HEMT Noise Neural Model Based on Bias Conditions", *The Int. Journal for Computation and Mathematics in Electrical and Electronic Engineering - COMPEL*, Vol. 23 No.2, 2004, pp.426-435.

[12] V. Marković, O. Pronić, Z. Marinković, "Noise Wave Modeling of Microwave Transistors Based on Neural Networks", *Microwave and Optical Technology Letters*, Vol. 41 No. 4, 2004, pp. 294-297.

[13] D. Pozar, *Microwave Engineering*, John Wiley & Sons, Inc., New York, 1998.

[14] http://www.semiconductor.agilent.com