# ANNs in Bias Dependent Scalable Modeling of HEMT S-Parameters

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*Abstract* – **An efficient procedure for modelling of scattering parameters for a class of microwave FETs manufactured in the same technology is presented in this paper. It is based on multilayer perceptron artificial neural network (ANN) that produces scattering parameters at its outputs for device gate width, biases and frequency presented at its inputs. After the ANN training, the scattering parameters' prediction under different operating conditions for any device from the class requires only calculation of the ANN response, without changes in the ANN structure. Numerical examples for *S* parameters modeling for one specific series of pHEMT devices are shown.**

*Keywords* – **Artificial neural network, scattering parameters, pHEMT**

## I. Introduction

In the last decade some attempts have been made to model devices and systems in the area of microwaves by using artificial neural networks, [1]-[7]. Unlike complex 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 the 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 to provide the correct response even for the input values not presented during the training process. In that way, the developed models can be used for a reliable prediction over a wide range of input parameters.

The characterization of microwave FETs (MESFET, HEMT) includes knowledge about device signal and noise parameters that are frequency-, temperature- and bias-dependent. Since measurements of these parameters, especially of noise parameters, are complex and time-consuming procedures, device models are usually used for device *S*- and noise parameters' prediction in the microwave circuit design.

According to the recent research, neural networks seem to be good alternative to conventional transistor modeling. They enable transistor signal and noise modeling versus biases and/or temperature and frequency ([2], [3], [5]-[7]) in the whole device operating range. However, these models are valid for the considered device only.

In this paper, a problem of bias-dependent *S*- parameters prediction for different-gate-width microwave FET transistors is considered. The modeling procedure proposed here is an extension of the method presented earlier in [5]-[7]. The ANN inputs are not only biases and frequency, but also device gate-width, therefore the proposed ANN model is valid for a whole class of devices made in the same technology.

The paper is organized as follows. In Section II neural networks are shortly introduced. The transistor S- parameters modeling procedure based on ANNs is stated in Section III. Some modeling examples and the main results are presented in Section IV. Finally, in Section V, the main conclusions are reported.

## II. Multilayer Neural Networks

A standard multilayer perceptron (MLP) neural network is shown in Fig.1. [1].

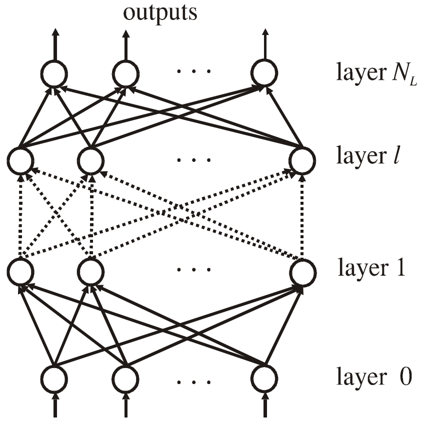


Fig. 1. MLP neural network

This network consists of an input layer (layer 0), an output layer (layer $N_L$), as well as several hidden layers.

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:

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

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.

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The 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 device 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 is the whole training set processing) is reached. Once trained, the network provides fast response for various input vectors (even for those not included in the training set) without additional optimizations.

## III. Transistor S- Parameters Modeling Based on ANNs

A problem of bias dependent transistor scattering paremeters' prediction for different gate widths is considered.

Recently, bias-dependent scattering parameters' modeling of microwave FETs' by using of neural networks have been proposed [6], [7]. This model is an MLP neural network that gives values of the S- parameters for given bias conditions (dc drain-to-source voltage, $V_{ds}$, and dc drain-to-source current, $I_{ds}$) and frequency, $f$, at its input neurons. The model is valid for the modeled device only. In order to extend its validity to a class of transistors, the transistor gate width, $W$, is proposed to be an additional input into the neural model. Therefore, the model proposed here (Fig 2) 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. For 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.

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

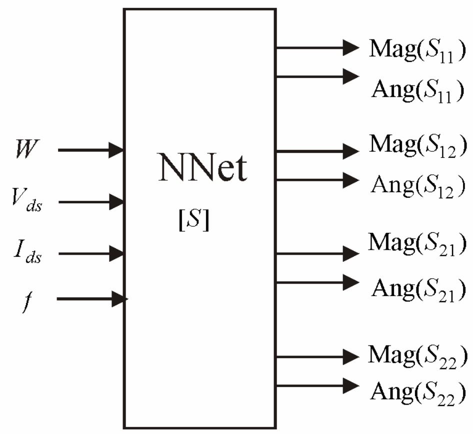


Fig. 2. Proposed ANN model

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 values. A correlation coefficient near one indicates an excellent predictive ability, while a coefficient near zero indicates poor predictive ability.

## IV. Numerical Results

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 [8]. These data refer to certain number of bias points. The S- parameters are available in (0.5-18) GHz frequency range for 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.

During the training process, ANNs are trained to satisfy a priori given accuracy. In order to illustrate quality of learning the training data, a scatter plot of neural model output vs. reference values for the magnitude and angle of $S_{12}$ parameter, referring to the training biases, is shown in Fig. 3 and Fig. 4, respectively. Data points very close to a straight line along the diagonal axis indicate good predictive accuracy.

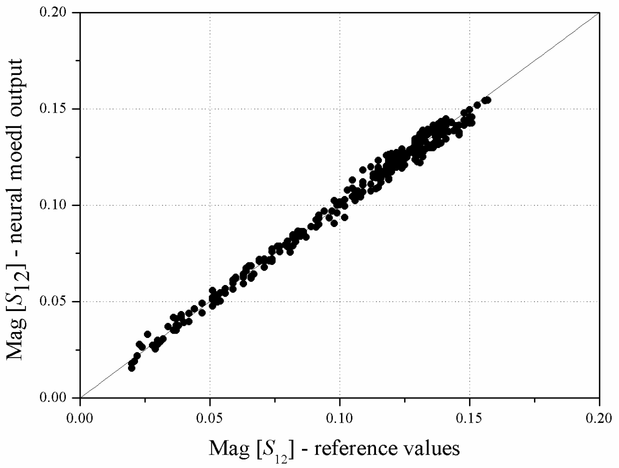


Fig. 3. Magnitude of $S_{12}$ – a scatter plot of neural model output vs. reference values (for the training biases)

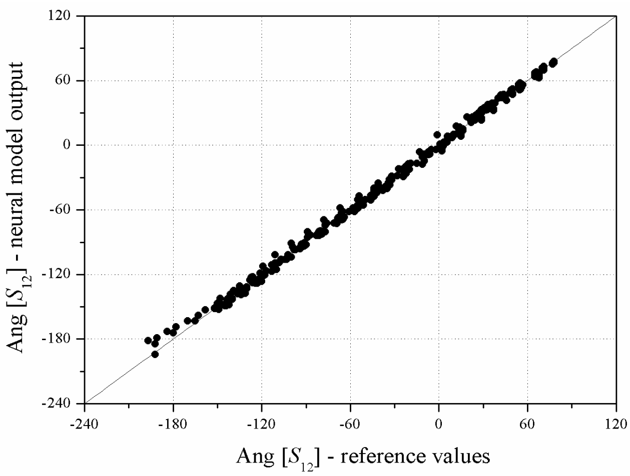


Fig. 4. Angle of $S_{12}$ – a scatter plot of neural model output vs. reference values (for the training biases)

Further, in Tables I and II there are results of the test process for *S*-parameters for the training values as well as for the test values not included in the training set . In Table I there are statistic data for the bias points used in the training process. 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, either for input values used as the training data or for those presented to the ANN for the first time during the test process.

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

| | ATE[%] | WCE[%] | $r$ |
|---|---|---|---|
| $\lvert S_{11} \rvert$ | 1.8132 | 7.0316 | 0.99628 |
| $Ang(S_{11})$ | 1.2605 | 4.6728 | 0.99859 |
| $\lvert S_{21} \rvert$ | 1.1543 | 7.0788 | 0.99708 |
| $Ang(S_{21})$ | 0.9563 | 3.0278 | 0.99912 |
| $\lvert S_{12} \rvert$ | 1.9544 | 6.8694 | 0.99526 |
| $Ang(S_{12})$ | 0.9373 | 5.5646 | 0.99891 |
| $\lvert S_{22} \rvert$ | 1.4566 | 8.1647 | 0.99728 |
| $Ang(S_{22})$ | 1.7406 | 7.7594 | 0.99699 |

Table II. Testing results for the bias points not used in the training process ATF35143 (2V, 15mA)

| | ATE[%] | WCE[%] | $r$ |
|---|---|---|---|
| $\lvert S_{11} \rvert$ | 1.4878 | 3.1918 | 0.99845 |
| $Ang(S_{11})$ | 1.0633 | 2.0011 | 0.99952 |
| $\lvert S_{21} \rvert$ | 3.2862 | 10.3900 | 0.99520 |
| $Ang(S_{21})$ | 1.1073 | 2.30264 | 0.99984 |
| $\lvert S_{12} \rvert$ | 3.7799 | 7.00619 | 0.99828 |
| $Ang(S_{12})$ | 1.6385 | 2.76736 | 0.99973 |
| $\lvert S_{22} \rvert$ | 3.5683 | 9.68265 | 0.99131 |
| $Ang(S_{22})$ | 3.2738 | 6.52157 | 0.99859 |

As a further illustration, in Fig. 5, 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 a fact that the predicted values match very well to the referent ones, it can be confirmed that very good generalization has been achieved.

## V. Conclusion

A bias dependent signal model of microwave MESFETs / HEMTs scaling with the device gate width is proposed in this paper. It is a multilayer perceptron neural network trained with the aim to learn *S* parameters' dependence on gate width, bias conditions and frequency. The network is trained using measured values of *S* parameters for several different gate width devices produced in the same technology. Once the network is trained its structure remains unchanged. After the training, the *S* parameters determination is done without additional optimizations.

The proposed neural model is able to predict *S*- parameters with a good accuracy for any given bias and frequency point from the device operating range, either for those used for the network training or for those presented to the network for the first time, as it is illustrated by numerical examples.

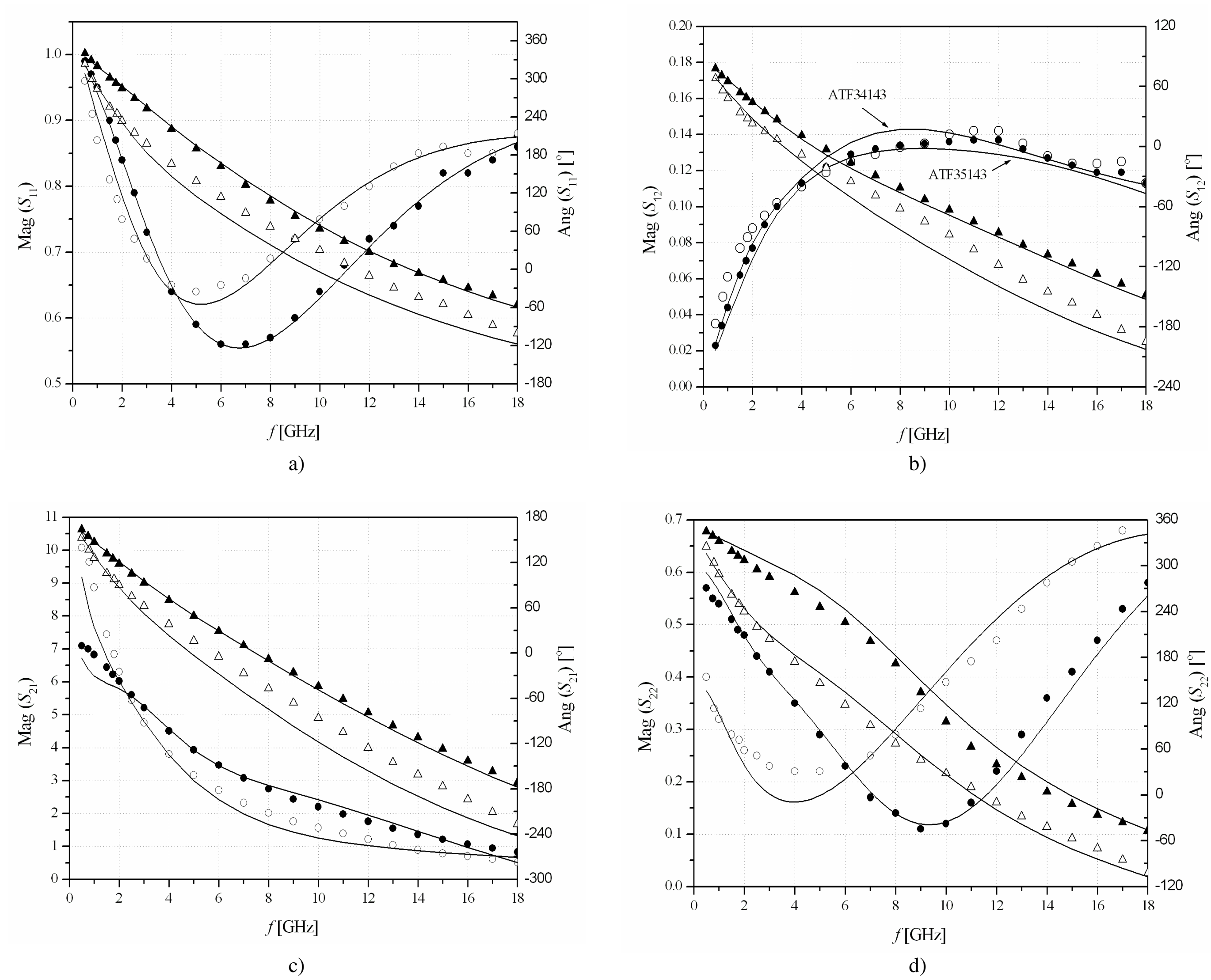


Fig. 5. Magnitudes (circles) and angles (triangles) of scattering parameters for bias points not used for the training process (black symbols – ATF35143 (2V, 15mA) ; white symbols - ATF34143 (3V, 20mA); solid lines – neural model output) a)$S_{11}$ b) $S_{12}$ c) $S_{21}$ d) $S_{22}$

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