Prediction of HEMT's Scattering and Noise Parameters using Neural Networks

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Abstract- **Recently, neural networks have been applied in modeling of microwave transistor noise dependence on frequency and bias conditions. The aim of this paper is to present a way for improving the modeling process for the noise parameters with very irregular behavior. Improving is achieved by model decomposition and introducing S-parameters as additional inputs of neural networks modeling irregular parameters. In addition, S-parameters itself have been modeled using neural networks.**

Keywords - **Neural networks, microwave transistors, noise parameters, S-parameters**

I. INTRODUCTION

Low noise microwave transistors (MESFET, HEMT, HBT, etc.) are applied in many modern communication systems where a low noise level is required. Therefore, transistor noise characterization is very important for the fast and reliable design of such systems. Since the measurement procedures of noise parameters are complex and time-consuming [1], there are many attempts to develop the appropriate noise models of microwave transistors. It should be noted that most of the existing empirical or physical models are limited to one bias point.

As highly nonlinear structures, neural networks are able to model nonlinear relations between different data sets. Owing to this ability, they have been applied in a wide area of problems. Especially, they are interesting for problems not fully mathematically described. Once trained they can predict response with quite a good accuracy, even for input values not presented in the training process, without changes in their structure and without additional knowledge of considered problem. Neural models are simpler than physically based ones but retain the similar accuracy. They require less time for response providing; therefore using of neural models can make simulation and optimization processes less time-consuming, shifting much computation from on-line optimization to off-line training.

Recently, neural networks have been applied in the microwave area [3]. Neural models of passive components are presented in [4], [5]. There are some neural models that refer to the microwave transistors, [5]-[9].

Recently, the authors of this paper have developed several new noise models of microwave transistor based on neural networks [2] that are not limited to single bias conditions. Further improvements, intended to make noise modeling by neural networks more accurate, are presented in this paper. A complete model giving all noise parameters, as well as S parameters will be proposed.

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II. TRANSISTOR NOISE

Any two-port noisy component can be characterized by a noise figure F, which is a measure of the degradation of the signal-to-noise ratio between input and output of the component, [1], and can be expressed as

$$F = F_{\min} + \frac{4R_n\left|\Gamma_g - \Gamma_{opt}\right|^2}{Z_0\left(1-\left|\Gamma_g\right|^2\right)\left|1+\Gamma_{opt}\right|^2},$$

where $F_{\min}$ is a minimum noise figure, R_n is an equivalent noise resistance, Γ_{opt} is the optimum reflection coefficient, and finally, Z_0 is normalizing impedance. The optimum reflection coefficient refers to the optimum source impedance that results in minimum noise figure, $F = F_{\min}$. The noise parameters $F_{\min}$, Γ_{opt} and R_n describe inherent behavior of the component and are independent of a connected circuit.

III. TRANSISTOR NOISE MODELING USING MULTILAYER NEURAL NETWORK

The basic idea of neural network application in microwave transistor noise modeling is developing of appropriate noise models that can accurately predict transistor noise parameters in a wide frequency range for all bias points from the operating range. As a first step, transistor noise parameters dependence on biases and frequency is modeled using multilayer perceptron network – MLP. A standard MLP neural network is shown in Fig.1. [3].

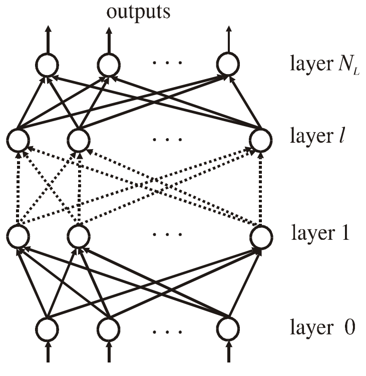

Fig.1. *MLP neural network*

This network consists of neurons (circles) grouped into the layers. The input signal is presented to the neurons from the input layer. Each neuron from one layer is connected to all neurons from the next layer. The output layer neurons represent outputs of the network. The layers that are not directly connected to the outside environment are hidden layers. Neurons are characterized by their activation functions. Here, a linear function for input and output layer and a sigmoid function for hidden layers are chosen. The connections between neurons are characterized by weighting factors.

Input vectors are presented to the input layer and fed through the network that then yields the output vector. Network training is a process of adjusting of network parameters (activation function thresholds and connection weights) in order to minimize the difference between a network response and reference values. This process is iterative and it proceeds until errors are lower than the prescribed goals or until the maximum number of epochs (epoch - the whole training set processing) is reached. Here, for training purposes, *Levenberg-Marquardt* algorithm (a modification of "backpropagation" algorithm) is used.

MLP networks are applied with the aim to model the HEMT transistor noise parameters dependence on frequency and bias conditions (dc drain-to-source and dc drain-to-source current). The used MLP network structure has four layers (i.e. two hidden layers). There are three neurons in the input layer (Fig.2, *bf* mark stems from networks inputs: biases&frequency) corresponding to:

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

The output layer consists of four neurons corresponding to:

- minimum noise figure,
- magnitude of optimum reflection coefficient,
- angle of optimum reflection coefficient and
- normalized equivalent noise resistance (50 Ω normalizing impedance).

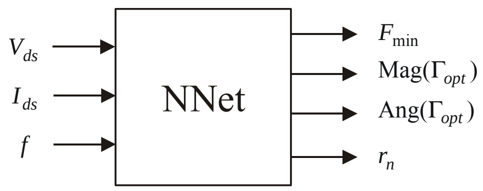

Fig. 2. *Neural model for noise parameters dependence on bias conditions and frequency (bf approach)*

Further, in order to improve modeling of parameters with irregular behavior (normalized equivalent resistance in most cases), a decomposition of the model is done and transistor scattering parameters are introduced as additional inputs of the neural network modeling critical parameter as it is shown in Figure 3, [2].

Obtained models are able to predict noise parameters with a good accuracy for a given bias point even in the case of the bias point not presented in the training process, without additional computation or change in the network structure.

Although S-parameters easier to be measured than noise parameters much time can be saved using neural models of S-parameters as well. At that way, all noise parameters can be predicted with high accuracy without additional measuring of S-parameters or their determination by simulation. This approach is presented in Figure 4.

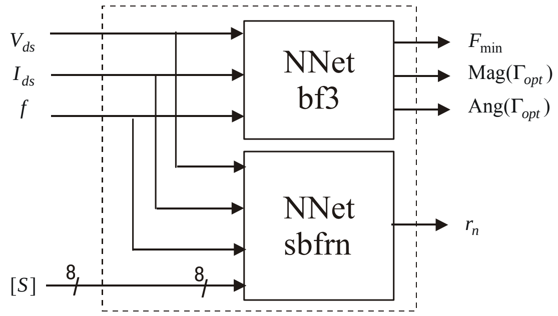

Fig. 3. *Neural model for noise parameters dependence on bias conditions, frequency (bf3-sbfrn approach)*

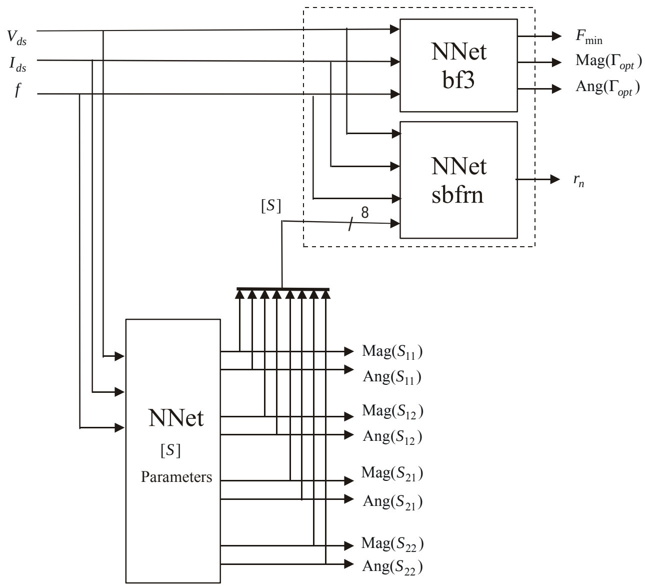

Fig. 4. *Neural model for accurate noise parameters prediction*

To quantify models' accuracy average test error (ATE [%]), worst-case error (WCE [%]), and correlation coefficient r between the reference and the modeled data were calculated for the training values and test values completely different from the training ones, [3]. The Pearson Product-Moment correlation coefficient r is defined by:

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

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

IV. MODELING EXAMPLE

In this section, the noise modeling of *Hewlett Packard's* pHEMT ATF-35143 will be presented. The modeling is done in the frequency range (0.5-10) GHz. The noise parameters values used for the training data are taken from manufacturer WEB site [10]. As it is presented in [2], after training process the best-obtained models are chosen. The best model for the minimum noise figure and magnitude and angle of optimum reflection coefficient is bf3_10_10. The best results for the normalized equivalent noise resistance give sbfrn_8_4 model. The fist model have 10 neurons in each of two hidden layers and the second 8 neurons in the first and 4 neurons in the second hidden layer (observed from input to the output).

Further, using the S-parameter data from the manufacturers web site neural models of S-parameter dependence on bias conditions and frequency are trained. These models have three input neurons corresponding to bias conditions and frequency (like bf3 models) and eight output neurons corresponding to magnitudes and angles of S-parameters. As the best model, sp_10_10 model containing 10 neurons in each of two hidden layers is chosen.

The next step was testing of the noise prediction. First, minimum noise figure and magnitude and angle of the optimum reflection coefficient were simulated using bf3_10_10 model. The simulation was done for biases used for the training as well as for the bias points not used in the training process. The test statistics is shown in Table I. It can be observed that WCE is less than 2% and ATE less than 1% in the case of training biases at the network input, meaning that the network learnt training data very well. The correlation coefficient close to one confirms this observation. In the case of model testing for the input values not used for the training WCE and ATE are greater and correlation coefficients are smaller than in the previous case but are still quite acceptable (WCE less than 3% and ATE les than 1.5%). It means that this model can predict very accurately noise parameters for the all operating bias conditions. As an illustration, the simulated noise parameters for a bias point not used in the training process are shown the Figures 5a, 5c and 5d as solid lines with circles and compared with reference values (dots).

Further, normalized equivalent noise resistance prediction by sbfrn_8_4 model was also done for training bias points and for the bias points not used for the training. In the first case, the manufacturer's S-parameter data, and in the second case, modeled S-parameter data are presented to the network. The comparison of normalized equivalent noise resistance prediction for the bias point not used in the network training is shown in Fig. 5b. It can be observed that predicted values in the case of manufacturer data at the network inputs (doted line with triangles) are very close to the reference values (black dots). Also, it can be seen that using of neural models of S-parameters does not cause significant degradation of the prediction. The test statistics shown in Table I confirm the previous conclusion.

V. CONCLUSION

Fast and efficient low-noise design requires the microwave transistor models that can predict noise parameters in a wide frequency range. In this paper, a possible approach to the noise parameters modeling is proposed. This approach in based on the use of neural networks. Neural networks are trained with the aim to learn noise parameters dependence on bias conditions and frequency. In order to improve modeling of parameters with irregular behavior, model decomposition is done. Therefore these critical parameters (mostly equivalent noise resistance) are modeled using a separate neural network that has transistor scattering parameters as additional inputs as well. Further, S-parameters dependence on bias conditions and frequency is also modeled using neural networks. The final transistor noise model consists of three neural networks. Using this model, the noise prediction process becomes very simple, including only the computation of the neural network response for desired frequency and bias conditions. It is important to note that the prediction is very accurate not only for the biases used for the training process but also for the completely different ones. In such way, noise parameters can be predicted for all operating bias points.

TABLE I. TESTING PROCESS STATISTICS

	Training values			Values not used for training		
	ATE[%]	WCE[%]	r	ATE[%]	WCE[%]	r
bf3_10_10						
F_{min}	0.360875	1.69595	0.999728	1.03347	2.96388	0.999891
$\lvert\Gamma_{opt}\rvert$	0.505099	1.3379	0.999808	1.00738	1.81556	0.999635
$Ang(\Gamma_{opt})$	0.323535	1.04238	0.999911	1.23896	2.33307	0.999851
sbfrn_8_4 : manufacturer S-parameter values at the network input						
r_n	0.103497	0.660071	0.99993	5.79087	28.5683	0.949293
sbfrn_8_4 : modeled S-parameters at the network input (sp_10_10 neural model)						
r_n	0.908401	11.8411	0.994026	7.06242	29.4353	0.938127

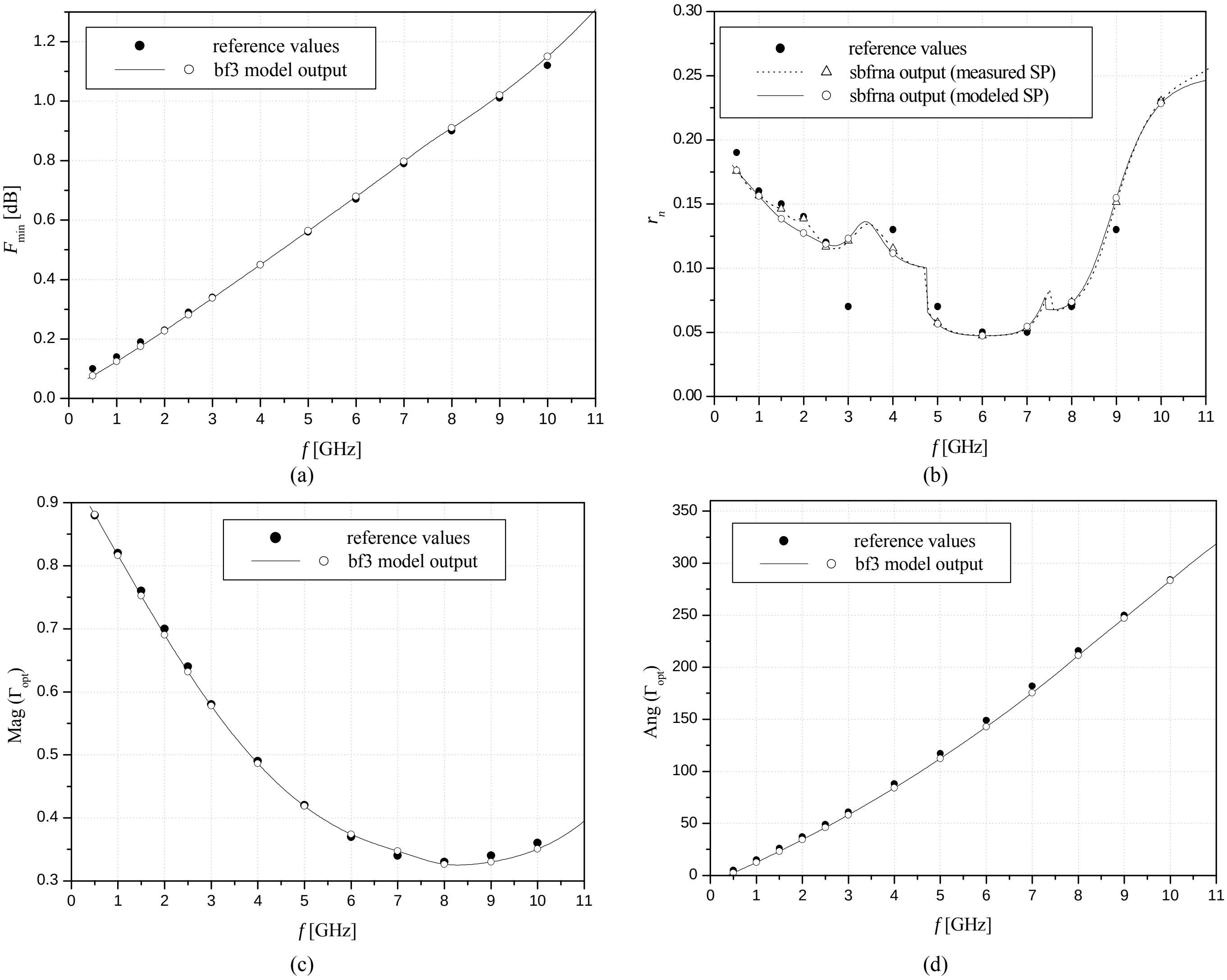

Fig. 5. *Comparison of generalization capabilities of the bf_10_10 and sbf_10_10 models (a) minimum noise figure; (b) normalized equivalent resistance; (c) magnitude of optimum reflection coefficient; (d) angle of optimum reflection coefficient*

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