ANNs in Bias Dependant Small-Signal and Noise Modeling of Microwave FETs

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***Abstract* — In this paper an efficient procedure for determination of small-signal and noise behavior of microwave transistors for various bias conditions is proposed. An empirical transistor noise model based on an equivalent circuit (improvement of Pospieszalski's noise model) is considered. Since it is necessary to extract values of the model equivalent circuit for each bias point (which requires the measured data acquiring and repeated time consuming extraction procedures), it is proposed to use an artificial neural network to model the bias dependence of the equivalent circuit parameters. In that way, it is necessary to acquire the measured data and extract the equivalent circuit parameters only for several operating biases used for the network training. Once the neural network is trained, the device small-signal scattering and noise parameters are easily obtained for an arbitrary bias point from the device operating range without changes in the model. The proposed modeling approach is exemplified by modeling of a specific MESFET device in a packaged form.**

***Keywords* — artificial neural network, microwave transistor, signal and noise modeling, bias conditions.**

I. Introduction

TODAY'S wireless communication systems require transceiver circuits with an appropriate dynamic range and good sensitivity – the performances that depend to a great extent on the RF noise and linearity of the transistors used in these circuits. Therefore, reliable and accurate small signal and noise models of low noise microwave FETs (MESFETs, HEMTs) are required for the design of active circuits in modern communication systems.

During the last few decades extensive work has been carried out in the field of signal / noise modeling of microwave transistors. Their physical models are complex and require many input technological parameters, [1] - [2], therefore the empirical models, mostly based on equivalent circuit representations, are usually used, as more convenient, for a device signal and noise prediction in the microwave circuit design, [3] – [5].

Most of the existing transistor noise models are valid only for a specific temperature and bias point. For each operating point, the noise parameters have to be determined at, it is necessary to repeat extraction of the noise model parameters from the measured data. It is basically an optimisation process, usually time-consuming. Moreover, the experimental data acquiring makes the extraction process more complex since it requires sophisticated measurement procedures, especially in the case of noise characterisation.

A noise modeling approach proposed in [6] and [7], provides an accurate prediction of the noise parameters of microwave MESFETs/HEMTs for various device operating conditions (ambient temperatures, bias) introducing noise corrections error functions valid for all operating points, but repeated extractions of equivalent circuit parameters are still requested.

The mentioned "measurement and optimisation" problems can be overcome using artificial neural networks (ANN), as it is proposed here. The artificial neural networks have been chosen as a modeling tool since they have an ability to learn from the presented data, and therefore they are especially interesting for problems not fully mathematically described. There are many publications reporting the results of applications of the neural networks in the microwave area, [8]-[15]. Neural networks have been applied in modeling of either active devices or passive components, in microwave circuit analysis and design, etc.

In this paper, dependence of microwave FETs' small-signal scattering (S-) parameters and noise parameters on bias conditions (bias current) is considered. It is proposed to use an ANN to model dependence of transistor equivalent circuit parameters on the bias current. The values of the equivalent circuit parameters (ECPs) obtained by ANN are further used in the circuit simulator to determine the device scattering and noise parameters.

The paper is organized as follows. The considered empirical noise model of microwave FETs is described in Section II. ANNs are shortly introduced in Section III. The proposed bias dependent signal and noise model of microwave FETs and its implementation in standard microwave simulators are described in Section IV. Validity of the proposed modeling approach is verified by the appropriate modeling examples given in Section V. The main conclusions are reported in Section VI.

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II. Empirical Noise Model

The two-parameter Pospieszalski`s noise model [3] is considered to be the most suitable one for implementation into the standard commercial microwave circuit simulators. The equivalent circuit of a MESFET/HEMT package including noise sources according to the approach presented in [3] is shown in Fig. 1. Transistor intrinsic circuit, which is common for the most of microwave FET models, is denoted by the dashed line. The remaining extrinsic elements, embedded in the circuit, represent parasitic effects of device. The resistors R_{gs} and R_{ds} determine thermal noise of intrinsic circuit. In MESFET noise model [3], the equivalent gate noise temperature, T_g, and drain noise temperature, T_d, are assigned to these resistances. The noise contributions of these resistors are represented by the voltage noise source e_{gs} and the current noise source i_{ds}, respectively.

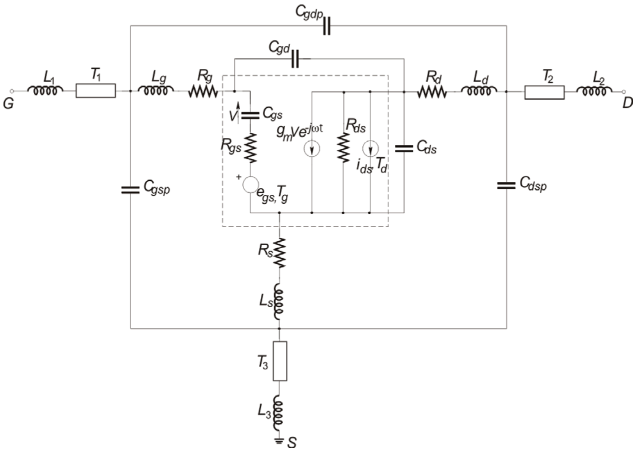

Fig. 1. Equivalent circuit of MESFET / HEMT package including noise sources.

The noise parameters of transistor intrinsic circuit calculated according to the Pospieszalski`s approach are: minimum noise figure $F_{min,p}$, optimum source reflection coefficient $\Gamma_{opt,p}$ and noise resistance $R_{n,p}$. They are functions of transistor intrinsic circuit elements and equivalent gate and drain noise temperatures and can be determined as follows, [3]:

$$F_{min,p} = 10 \cdot \log\left(1 + \frac{T_{min,p}}{T_0}\right), \tag{1}$$

$$T_{min,p} = 2\frac{\varpi C_{gs}}{g_m}\sqrt{R_{gs}T_g G_{ds}T_d + \left(\frac{\varpi C_{gs}R_{gs}G_{ds}T_d}{g_m}\right)^2} + \left(2\frac{\varpi C_{gs}}{g_m}\right)^2 R_{gs}G_{ds}T_d, \tag{2}$$

$$R_{n,p} = \frac{T_g}{T_0}R_{gs} + \frac{G_{ds}T_d}{g_m^2 T_0}\left(1 + \varpi^2 C_{gs}^2 R_{gs}^2\right)^2, \tag{3}$$

$$\Gamma_{opt,p} = \frac{R_{opt,p} + jX_{opt,p} - Z_0}{R_{opt,p} - jX_{opt,p} + Z_0}, \tag{4}$$

$$R_{opt,p} = \sqrt{\left(\frac{g_m}{\varpi C_{gs}}\right)^2 \frac{R_{gs}T_g}{G_{ds}T_d} + R_{gs}^2}, \tag{5}$$

$$X_{opt,p} = \frac{1}{\varpi C_{gs}}, \tag{6}$$

where T_0=290 K is the reference noise temperature and Z_0=50 Ω.

However, the transistor noise parameters calculated according to the noise model [3] do not perfectly match the measured noise parameters. The Pospieszalski’s noise model accuracy could be improved in a way authors proposed earlier in [6]-[7] and described briefly below.

In order to minimize deviations that exist between measured and simulated noise parameters, a correction procedure based on incorporation of frequency-dependent error correction functions into the noise equations (1)-(6) is derived. First, for each of four noise parameters, the ratio of the experimental and simulated noise parameter values is calculated over the entire frequency range. Then, a curve fitting procedure is applied on these sets of data, in order to obtain suitable frequency dependences. In this way, corresponding mathematical functions are chosen for all four noise parameters for the intrinsic circuit. The obtained functions represent error correction functions for accuracy improving of the Pospieszalski's noise model. Namely, each intrinsic circuit noise parameter obtained by approach proposed in [3] is multiplied by the corresponding error correction function $y_i(f)$, i=1, 4. As a result, new equations for transistor intrinsic circuit noise parameters become:

$$F_{min} = F_{min,p} \cdot y_1(f) \tag{7}$$

$$Mag(\Gamma_{opt}) = Mag(\Gamma_{opt,p}) \cdot y_2(f), \tag{8}$$

$$Ang(\Gamma_{opt}) = Ang(\Gamma_{opt,p}) \cdot y_3(f), \tag{9}$$

$$r_n = r_{n,p} \cdot y_4(f). \tag{10}$$

By applying the set of equations (7)–(10), improved modeling of MESFET/HEMT noise parameters is achieved. The error correction functions determined for one operating temperature or bias point are valid for the whole device operating range.

By using the above described approach, it is necessary to repeat extraction of ECPs for each new bias point from the device operating range. Since it implies complex acquiring of measured data and an optimisation as well, in order to increase efficiency of the considered method, artificial neural networks are proposed to be applied for the extraction of ECPs in the whole operating range of biases.

III. Multilayer Perceptron ANN

A standard MLP (*Multilayer Perceptron Network*) is used in this paper. It consists of neurons grouped into layers (an input layer, an output layer, as well as several hidden layers), [8]. Each neuron from one layer is connected to all neurons from the next layer, but there are no connections among neurons in the same layer. Each neuron is characterized by an activation function and each connection between neurons is characterized by a weight. The MLP network is a *feed forward* structure, meaning that input signals are presented to the neurons in the input layer and fed through the network to the output layer neurons. Responses of the output neurons yield the output data vector.

The neural network „learns” the relationship among the sets of input-output data (training set) by adjusting neural network parameters (connection weights and biases of activation functions) in order to minimize difference between the desired values and neural network obtained values. During this training process, at the beginning, input vectors are presented to the input neurons and output vectors are computed. Further, partial derivatives of the difference between the desired values and neural network obtained values are calculated for each sample from the training set and used for updating the weights and biases of the neurons.

The training process proceeds until errors are lower than prescribed values or until a maximum number of epochs (epoch is the whole training set processing) is reached. The most common training algorithms are based on *backpropagation* algorithm, and its modifications, [8]. Once trained, the network provides a fast response for all vectors from the input space without any additional change of its structure or its parameters. Furthermore, it provides a correct response for the input values completely different from training ones, i.e. it has a generalization capability.

In order to quantify accuracy of an ANN model, average test error (ATE [%]), worst-case error (WCE [%]), and correlation coefficient, r, between the referent and the modeled data are calculated, [5].

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

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \tag{11}$$

where x_i is a referent value, y_i is the ANN 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 a poor predictive ability.

IV. Proposed Model

The proposed small-signal and noise model of microwave FETs consists of an empirical transistor noise model based on an equivalent circuit representation and an additional artificial neural network developed for modeling bias dependences of ECPs, as illustrated in Fig.2.

For the purpose of the ECP determination for various bias conditions an MLP neural network with one hidden layer is used. Since we considered the case where dc drain-to-source voltage is constant, the ANN (shown in Fig. 3) has one neuron in the input layer corresponding to dc drain-to-source current, I, while the number of the neurons in the output layer corresponds to the number of ECP (let this number be denoted as N).

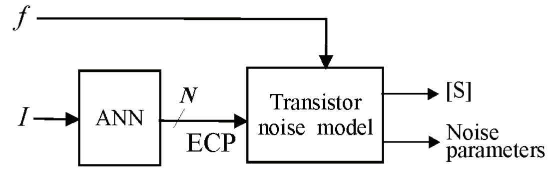

Fig. 2. Proposed bias-dependent model.

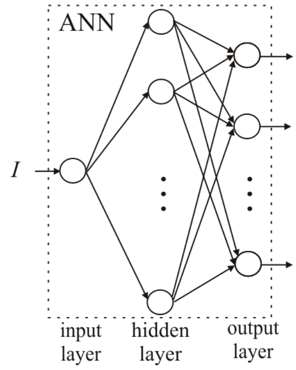

Fig. 3. MLP ANN for ECP determination.

Neurons from the input and output layers have linear activation functions and hidden neurons have a sigmoid activation function,

$$F(u) = \frac{1}{1+e^{-u}} \,. \tag{12}$$

Therefore, values of the ECP can be obtained according to the following matrix equation

$$\mathbf{ECP} = \mathbf{W_2} * F(\mathbf{W_1} * I + \mathbf{B_1}) + \mathbf{B_2}\,, \tag{13}$$

where $\mathbf{W}_1$ and $\mathbf{W}_2$ are weight matrices between the input and the hidden layer and between the hidden layer and the output layer, respectively, and $\mathbf{B}_1$ and $\mathbf{B}_2$ are bias matrices for the hidden and the output layer, respectively.

The neural network is trained by using extracted ECP values for a certain number of bias currents. After the training is done, ECPs for any bias current from the device operating bias range are determined by simply calculating ANN response.

The training of the ANN is the first step in the model development. The model implementation in a standard microwave circuit simulator, such as ADS, [16], is done by assigning the trained ANN to the improved transistor noise model. Actually, after the training and evaluation of the ANN, a set of mathematical expressions describing the trained network is generated. This can be automated within the training software environment. Further, these expressions are put in a VAR (Variables and Equations) block within the schematic of the transistor equivalent circuit in the microwave simulator. Input of the VAR block is the same as the input of the neural network - a bias current value, while equivalent circuit parameters calculated from these expressions are VAR block outputs. The ECP values are assigned to the corresponding elements of the empirical model and used for the further S- and noise parameters’ simulation. In this way, for an arbitrary value of the bias current the S- and noise parameters can be easily determined without additional optimizations and measurements.

V. Experimental Results

The proposed modeling method was applied to a GaAs FET, type ATF21186 by Agilent (HP), and some of the obtained results are presented in this paper. The measured values of S- and noise parameters for bias currents: 10 mA, 15 mA and 20 mA (bias drain-to-source voltage is 2 V in all cases), in the frequency range (0.5–8) GHz, taken from the device datasheet, were used for the model development. All simulations were performed using a microwave circuit simulator ADS, [16].

First, the ECPs of Pospieszalski's transistor noise model have been extracted from the available measured data. Further, the appropriate error correction functions $y_i(f)$, i=1,4 have been determined for the bias point (2 V, 20 mA). The most suitable form of the error correction function $y_1(f)$ is the exponential one. The error correction functions $y_2(f)$, $y_3(f)$ and $y_4(f)$ have polynomial forms. The improved noise model with once determined error correction functions enables efficient noise modeling of the same transistor for other bias conditions.

Then, an ANN was trained to predict ECP dependence on bias current. This ANN has one input neuron (corresponding to bias current) and 26 output neurons (24 of them correspond to small-signal circuit elements and the rest two - to the equivalent gate and drain noise temperatures). The number of neurons in the hidden layer was determined through the training process. Namely, ANNs with different numbers of hidden neurons were trained and compared. The ECP values extracted from the above mentioned measured S- and noise parameters were used as the training data. A network with three hidden neurons was chosen as the best trained one and taken as the final model of ECPs' dependence on bias current.

Analysing the test statistics of the developed ANN, i.e. average test error, worst-case error and correlation coefficient calculated for all ECPs, it was found that ATE is lower than 0.1%, WCE is lower than 0.2%, while the correlation coefficient is greater than 0.9999. According to this, it can be considered that for the bias current values used for the model development (10 mA, 15 mA, 20 mA), the values obtained by the empirical model and by the proposed model are almost the same.

In order to confirm the previous, as an example, the magnitude of the transconductance, g_m, and drain noise temperature, T_d, obtained by this neural network plotted versus bias current, are shown in Fig.4.

Since the main goal here is modeling of the scattering and noise parameters, in Figs. 5-8 there are some of the results concerning the mentioned parameters.

A scatter plot of the proposed neural model output vs. reference values for F_{min} is shown in Fig. 5. It can be observed that data points do not disperse much from a straight line along the diagonal axis which indicates a good predictive accuracy.

In Figs. 6 - 8 there are some additional results where the scattering and noise parameters predicted by the proposed model are compared with the measured values.

Comparison of the measured and simulated results for the S_{21} parameter in frequency range (0.5-8) GHz for bias currents of 10 mA and 20 mA is shown in Fig. 6. Good agreement with measured results can be observed.

a)

b)

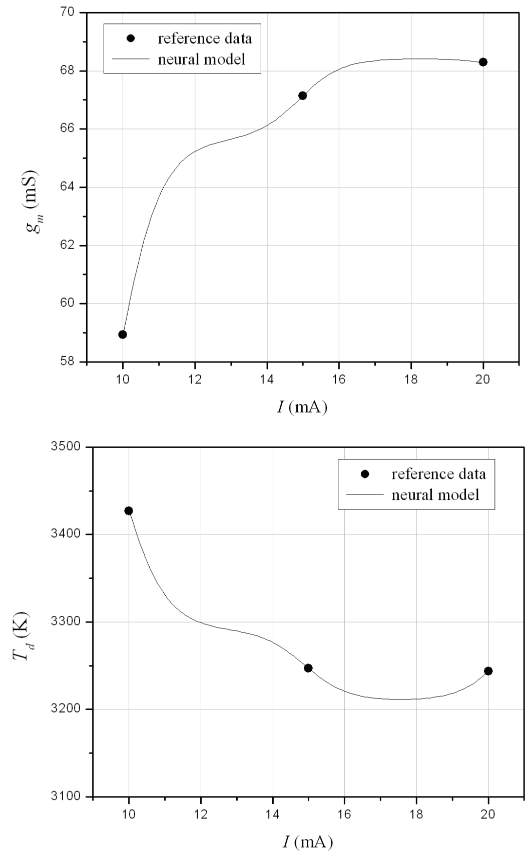

Fig. 4. Prediction of a) g_m and b) T_d.

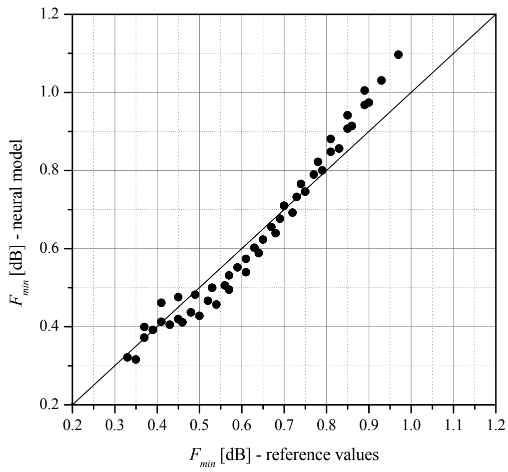

Fig. 5. Minimum noise figure – a scatter plot of neural model output vs. reference values.

In Fig. 7 and Fig. 8 there is the magnitude of optimum source reflection coefficient plotted versus the frequency and versus the bias current, respectively. Circles denote the measured (reference) values and solid lines – the simulated ones obtained by the neural model. It can be seen that the predicted values match well with the measured ones. The similar behavior is also obtained for the other noise parameters. Since, the ANN predicts ECPs with a high accuracy, deviations of the modeled values from the measured data are due to imperfections of the empirical model itself or imperfections of the extraction procedure.

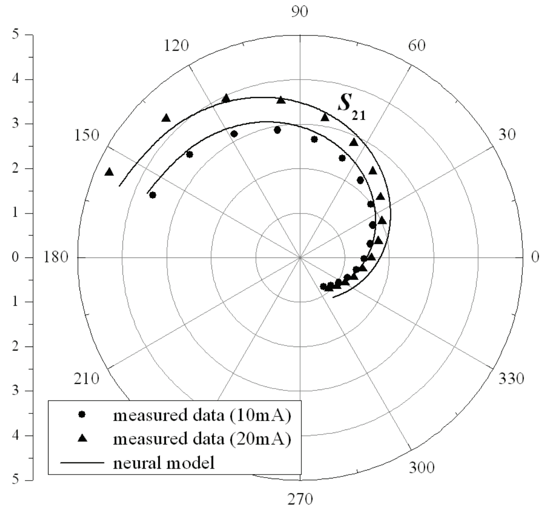

Fig. 6. Scattering parameter S_{21}.

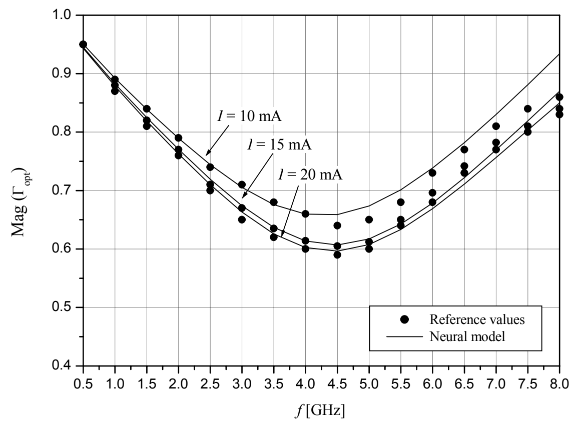

Fig. 7. Magnitude of optimum reflection coefficient vs. frequency.

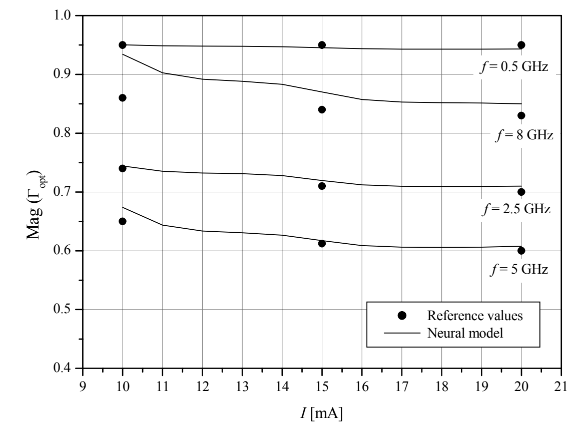

Fig. 8. Magnitude of optimum reflection coefficient vs. bias current.

VI. Conclusion

An efficient procedure for incorporating bias dependence into the noise models of microwave MESFETs / HEMTs based on an equivalent circuit is presented in this paper. In order to avoid repeated extractions of the equivalent circuit parameters an artificial neural network is proposed to model their dependence on bias conditions (only dependence on the bias current is considered here, the bias voltage is assumed to be constant). The network is trained using the extracted ECP values for a certain number of operating currents and then assigned to the device noise model. The considered empirical model is a modification of the Pospieszalski's noise model with the improved accuracy. The empirical model with the assigned neural network represents a single model valid for all considered biases and can be used as a new user-defined library element. According to the results obtained by applying the model to a particular device, it can be concluded that the proposed method provides an efficient way for accurate bias dependent determination of microwave transistor small-signal and noise performances. If the ANN is trained properly, the accuracy of the empirical model itself as well as the quality of the extraction of ECPs used for the ANN training have the most important impact on the accuracy of the proposed model.

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