# An Automated Procedure for MESFETs / HEMTs Noise Modeling Against Temperature

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Abstract - An automated procedure for accurate noise parameter prediction of microwave MESFETs / HEMTs against temperature is proposed in this paper. An improved modification of the Pospieszalski's noise model is used. The temperature dependences of the noise model elements are modelled using an artificial neural network. After training of the network and its assignment to the transistor noise model, noise parameters can be easily obtained for each temperature from the operating range without need for measured data. In that way, it is necessary to acquire the measured data and extract the elements only for a certain number of temperatures used for the network training. Furthermore, once developed model remains the same for all operating temperatures and therefore does not require additional optimizations and changes as the temperature changes.

*Keywords* - neural network, MESFET, HEMT, noise modelling.

## I. INTRODUCTION

Accurate small-signal and noise models of low noise microwave transistors (MESFETs and HEMTs) are very important for the computer-aided design of active circuits used in modern wireless systems. Hence, extensive work has been carried out in the field of signal and noise modeling of these devices. Since their physical models are too complex and require many input technological parameters, the empirical noise models are more often used, [1]-[3]. During the last decade, two-parameter Pospieszalski's noise model [3] turns out to be the most suitable one for implementation into the standard commercial circuit simulators This model generally shows good agreement with measured data, but some deviations can still be observed, since the correlation between two noise sources is completely ignored in this model. However, it has been found that the inaccuracy caused by this approximation is not negligible at higher frequencies. In [4], the correlation between the noise sources is taken into account by defining the third equivalent noise temperature, called the correlation temperature.

Further, transistor signal and noise characteristics are temperature and bias dependant, but most of the existing transistor noise models including the Pospieszalski's one, are valid only for specific temperature and bias point. Authors of this paper have proposed the procedure for accurate prediction of noise parameters of microwave MESFETs / HEMTs for various device ambient temperatures, [5]. A drawback of this model is that it is necessary to extract the elements of the model for each further temperature point. It is basically an

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Aleksandra Medvedeva 14, 18 000 Niš, Serbia and Montenegro e-mail: [zlatica,oljap, jovanar, vera]@elfak.ni.ac.yu optimisation process that can be time-consuming. Furthermore, the measured signal and noise data for each new temperature point are requested for the extraction, which could take much efforts and time, since the measurements, especially of the noise parameters, require complex equipment and procedures.

A new approach to overcoming these problems using artificial neural networks to model temperature dependences of model elements and parameters is proposed here. The artificial neural networks have been chosen as a modeling tool since they have the ability to learn from the presented data, and therefore they are especially interesting for problems not fully mathematically described. It should be noted that they fit non-linear dependencies better than polynomials. There are many papers referring results of applications of the neural networks in the microwave area, [6]-[10].

Development of the proposed model and its implementation in standard microwave simulators are described in the paper. An example of modeling the specific device is provided as well.

#### II. IMPROVED TRANSISTOR NOISE MODEL

The schematic of GaAs FET package model equivalent circuit including noise sources is shown in Fig.1. The intrinsic circuit, which is common for most of the transistor models, denoted by a dashed line, is embedded in a network representing device parasitics.



Fig.1. MESFET / HEMT package equivalent circuit including noise sources

The Pospieszalski's noise model, [3], is based on simple expressions for noise parameters of MESFET / HEMT intrinsic circuit as the functions of the equivalent circuit

parameters (ECP): transistor intrinsic circuit elements and equivalent gate and drain temperatures. However, the transistor noise parameters (minimum noise figure  $F_{min}$ , optimal source reflection coefficient  $\Gamma_{opt}$  and normalized noise resistance  $r_n = R_n / 50$ ) calculated in this way do not perfectly match measured noise parameters. The Pospieszalski's noise model accuracy could be improved in a way authors proposed earlier in [5]. In order to minimize deviations that exist between measured and modelled noise parameters, a correction procedure based on incorporation of frequency-dependent error correction functions into the noise equations is applied. Actually, the ratio of the experimental and simulated transistor noise parameter values is calculated for each of four noise parameters over the entire frequency range. Then, curve-fitting procedure is applied on these sets of data, in order to obtain suitable frequency dependences. In this way, corresponding mathematical functions are determined for all four noise parameters  $(F_{min}, Mag(\Gamma_{opt}))$ ,  $Ang(\Gamma_{opt})$  and  $r_n$ ). The obtained functions represent error correction functions for improving the Pospieszalski's noise

model. Namely, each intrinsic circuit noise parameter obtained by approach proposed in [3] is multiplied by corresponding error correction function and by using that new set of equations, more accurate prediction of noise parameters is achieved.

# III. ARTIFICIAL NEURAL NETWORK FOR THE ECP EXTRACTION

According to the above described approach, for each new temperature from the operating range it is necessary to repeat ECP extraction procedure. 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 ECP in the whole operating range of temperatures.

A standard MLP (*Multilayer Perceptron Network*) is suitable to be used for overcoming this problem. It consists of neurons grouped into layers (an input layer, an output layer, as well as several hidden layers), [6]. 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" relationship among 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 maximum number of epochs (epoch is the whole training set processing) is reached. The most common training algorithms are based on *backpropagation* algorithm, [6]. Once trained, the network provides fast response for all vectors from the input space without any additional change of its structure or its parameters. Furthermore, it provides correct response for the input values completely different from training ones, i.e. it has a generalization capability.

For the purpose of the ECP determination versus temperature an MLP neural network with one hidden layer is proposed (Fig.2). It has one neuron in the input layer corresponding to the ambient temperature (*T*), while the number of the neurons in the output layer corresponds to the number of temperature dependent ECP (let this number be denoted as *N*). Neurons from the input and output layers have linear activation functions and hidden neurons have sigmoid activation functions  $F(u) = 1/(1 + e^{-u})$ . Therefore, values of the ECP can be obtained according to the following matrix equation

 $\mathbf{ECP} = \mathbf{W}_2 * F(\mathbf{W}_1 * T + \mathbf{B}_1) + \mathbf{B}_2 \tag{1}$ 

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



Fig.2. MLP neural network for ECP determination

The network is trained using extracted ECP values for certain number of operating temperatures. After the training is done, ECP for any temperature from the operating temperature range are determined by simple finding neural network response.

## IV. MODEL IMPLEMENTATION IN A CIRCUIT SIMULATOR

The neural network developed in the proposed way is assigned to the improved transistor noise model described in the Section 2. The network assignment, i.e. its implementation in a standard microwave simulator such as ADS, [11] can be done as the following. At first, a set of expressions corresponding to the trained neural network is generated according to its structure and values of its parameters. 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 improved transistor model in the microwave simulator. The VAR block outputs are values of the ECP and they are assigned to the corresponding elements and parameters of the model and used for the further device noise simulation for any temperature and frequency from the operating range. The principle of the proposed noise parameters' determination is presented in Fig. 3.

In this way a new user-defined library element representing the considered device is created. Since the model has the temperature as an input it can be used for noise parameters' determination in the whole temperature range without changes in its structure and avoiding need for measured data acquiring and optimisation procedures.



Fig.3. Determination of the transistor noise parameters

#### V. NUMERICAL RESULTS

The proposed method has been applied to a packaged microwave HEMT, type NE20283, from NEC. Measured values of S and noise parameters over the temperature range from  $-40^{\circ}$ C to  $60^{\circ}$ C ( $20^{\circ}$ C step) have been used for the development of the model. These data have been obtained earlier at the University of Palermo, Italy [12].

First, the ECP of Pospieszalski's transistor noise model have been extracted from the available measured data, and the noise parameters are simulated. Further, for the temperature  $T=60^{\circ}$ C, the appropriate error correction functions for the noise parameters have been determined. As it has been shown in [5], the most suitable form of the error correction function is a polynomial form. It has been also shown that the proposed model with once determined error correction functions enables efficient noise modelling of the same transistor for various temperatures.

In order to increase the efficiency of the considered improved noise model, an MLP neural network is trained to predict ECP dependences on the temperature. According to Section 3 and as it has been referred in [13], this network has one input neuron, five hidden neurons and 20 output neurons. Nineteen of the output neurons correspond to 19 small-signal circuit elements and the last one to the equivalent drain temperature. The equivalent gate temperature is assumed to be equal to ambient temperature, [3]. The ECP extracted from the measured values of noise parameters have been used as the training data.

In Fig 4 there are examples of the temperature dependence prediction of the complex transconductance magnitude  $g_m$  and time delay  $\tau$  using this neural network.



Fig. 4. Prediction of the transistor model elements:  $g_m$  and  $\tau$ 



Fig.5. The magnitude of optimum reflection coefficient



In Figs. 5, 6 and 7 there are some results for the noise parameters obtained by the model shown in Fig.1 whose ECP are extracted using the neural network. The model accuracy improvement according to the procedure proposed in [5] is included too. The magnitude of optimum reflection coefficient versus temperature in the frequency range (6 - 18) GHz is shown in Fig 5. Frequency dependences of the minimum noise figure and the normalized equivalent noise resistance are shown in Figs. 6 and 7, respectively. Circles denote the measured values are solid lines values simulated from the

proposed model. It can be observed that the simulated values match well the measured values.



Fig.7. Equivalent noise resistance

# VI. CONCLUSION

An efficient procedure for incorporating temperature dependence into the noise models of microwave MESFETs / HEMTs is proposed in this paper. It is started from an earlier proposed accurate transistor noise model. As the temperature dependence is not incorporated directly in the model, for each operating temperature it is necessary to extract model elements and parameters (ECP) from the measured scattering and noise parameters. The extraction can be time consuming and the measurements require complex equipment and procedures. This problem is overcome by using an artificial neural network for modelling of temperature dependences of the ECP. The network is trained using the extracted ECP values for a certain number of operating temperatures. Once this network is trained its structure remains unchanged.

After the network assignment to the earlier proposed improved transistor noise model, a new user-defined library element representing the considered device in a standard circuit simulator is created and can be used for further noise analysis of the circuits that contain the device. Besides incorporating the temperature dependence in the model, this method provides results that agree well with measured characteristics.

#### ACKNOWLEDGEMENTS

This work has been supported by the Ministry of Science and Environmental Protection of Republic of Serbia under the project No. 101351. Authors would like to thank to Prof. Alina Cademmi, University of Messina, for providing the measured data used for this work.

#### REFERENCES

- M. S. Gupta, O.Pitzalis, S.E.Rosenbaum, P.T.Greiling, "Microwave Noise Characterization of GaAs MESFETs: Evaluation by On-Wafer Low-Frequency Output Noise Current Measurement", IEEE Trans. Microwave Theory Tech., vol. MTT-35, pp. 1208-1218, December 1987.
- [2] H. Fukui, "Design of Microwave GaAs MESFET's for Broadband Low-Noise Amplifiers", IEEE Trans. Microwave Theory Tech., vol. MTT-27, pp. 643-650, July 1979.
- [3] M. W. Pospiezalski, "Modeling of noise parameters of MESFET and MODFET and their frequency and temperature dependence" IEEE Trans. Microwave Theory Tech., vol. MMT-37, pp.1340-1350, Sept. 1989.
- [4] V. Marković, B. Milovanović, N. Maleš-Ilić, "MESFET Noise Model Based on Three Equivalent Temperatures", Proceedings of 27th European Microwave Conference, Jerusalem, Israel, 1997, pp. 966-971.
- [5] O. Pronić, G. Mitić, J. Ranđelović, V. Marković: "New procedure for accurate noise modelling of microwave FETs versus temperature", Electronics Letters, Vol.40, No.24, pp.1551-1553, 2004.
- [6] Q. J. Zhang, K. C. Gupta, Neural Networks for RF and Microwave Design, Artech House, 2000
- [7] P. M. Watson, K. C. Gupta, "Design and optimizacion of CWP circuits using EM-ANN models for CPW components", IEEE Trans., Microwave Theory Tech.,vol. 45, no. 12 pp. 2515-2523, 1997
- [8] G. L. Creech, B. J. Paul C. D. Lesniak, T. J. Jenkins, and M. C. Calcatera, "Artifical neural networks for fast and accurate EM-CAD of microwave circuits", IEEE Trans., Microwave Theory Tech., vol. 45, no. 5 pp. 794-802, 1997
- [9] 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.
- [10] 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
- [11] Advanced Desing System-version 1.5, Agilent Eesof EDA, 2000.
- [12] A. Caddemi, A. Di Paola, M, Sannino, "Microwave noise parameters of HEMTs vs. temperature by a simplified measurement procedure", Proceedings of EDMO96 Conference, Weetwood Hall, Leeds, 1996, pp. 153-157.
- [13] Z. Marinković, V. Marković, B. Milovanović, "Implementation of Temperature Dependence in Small-Signal Models of Microwave Transistors Including Noise", 24th Conference on Microelectronics MIEL 2004, Niš, Serbia and Montenegro, 2004, pp. 355-358.