# Accurate Temperature Dependent Noise Models of Microwave Transistors Based on Neural Networks

Zlatica Marinković, Vera Marković

Faculty of Electronic Engineering, University of Niš, Aleksandra Medvedeva 14, 18000 Niš, Serbia and Montenegro,
e-mail: zlatica@elfak.ni.ac.yu, vera@elfak.ni.ac.yu

***Abstract* — Recently, authors have proposed neural networks for modelling the temperature dependences of elements and parameters of microwave transistor small-signal equivalent circuit including noise. This neural model enables the prediction of modelled device noise parameters for any operating temperature. In this paper, an improvement of the neural model accuracy is proposed. It is done by using an additional neural network aimed to correct the noise parameters' values.**

## I. INTRODUCTION

During the last decade, neural networks have found many applications in modelling in the microwave area, [1]-[6]. Since they have the ability to learn from the presented data, they are especially interesting for non-linear problems and for the problems not fully mathematically described. Considered as a fitting tool, they fit non-linear dependencies better than polynomials do. Once trained, neural networks are able to predict outputs not only for the input values presented during training process (memorizing capability) but also for other input values (generalization capability). Neural networks have been applied in modelling of either active devices or passive components, in microwave circuit analysis and design, etc. It has have been proposed that they are applied in microwave MESFET and HEMT transistor signal and noise performance modelling, as well, [3]-[6].

Accurate and reliable noise models of microwave transistors are necessary for analyses and design of microwave active circuits that are parts of modern communication systems, where it is very important to keep the noise at a low level. Transistor signal and noise performances depend on the temperature, but most of the existing transistor signal, and especially noise models refer to a single temperature point (usually, nominal temperature). Therefore, for further analyses under various temperature conditions, it is necessary to develop models for each required operating temperature point. Model development is basically an optimisation process and can be time-consuming. Furthermore, measured signal and noise data for each new operating point are necessary for model development, which could take much effort and time, since these measurements require complex equipment and procedures.

Recently, neural networks have been proposed for modelling of the temperature dependences of elements and parameters of microwave transistor small-signal equivalent circuit including noise, [6], enabling prediction of the noise parameters in a circuit simulator in the whole operating temperature range. However, the accuracy of the neural model is limited by the accuracy of the chosen noise model. In this paper, improving the exactness of the model and overcoming the mentioned limitation are proposed and considered.

## II. MLP NEURAL NETWORK

An MLP (*Multilyer Perceptron Network*) consists of neurons grouped into one input layer, several hidden layers and one output layer. Each neuron from a layer is connected with all of the neurons from the next layer but there are no connections between the same layer neurons. An MLP network with one hidden layer (Fig.1) is suitable for the problems considered in this paper. Each neuron is characterized by an activation function and its bias, and each connection between two neurons by a weight factor. The neurons from the input and output layers have linear activation functions and hidden neurons have sigmoid activation function $F(u) = 1/(1+e^{-u})$.

Therefore, for the input vector $\mathbf{X}$, the neural network output vector $\mathbf{Y}$ can be obtained according to the following matrix equation

$$\mathbf{Y} = \mathbf{W_2} * F(\mathbf{W_1} * \mathbf{X} + \mathbf{B_1}) + \mathbf{B_2} \qquad (1)$$

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.

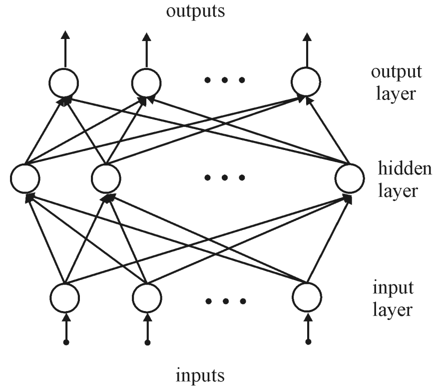


Fig. 1. MLP Neural Network

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) using optimisation procedures, such as the backpropagation algorithm or its modification – the Levenberg-Marquardt algorithm, [1]. Once a neural network is trained its structure remains unchanged, and it is capable of predicting outputs for all inputs whether they have been used for the training or not.

## III. Transistor Signal and Noise Characteristics

A microwave transistor is usually represented as a two-port circuit characterized by its scattering ([$S$]) matrix, that defines transistor signal performance. The [$S$] matrix consist of four complex scattering parameters, $S_{ij}$, $i,j$ = 1,2. In addition to the signal performance, any two-port noisy device 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 device, and can be expressed as

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

where $Z_0$ is normalizing impedance. In (2), minimum noise figure $F_{\min}$, equivalent noise resistance $R_n$, and magnitude and angle of the optimum reflection coefficient $\Gamma_{\text{opt}}$ represent a set of four noise parameters describing inherent behaviour of the device.

## III. Neural Noise Model

Recently, authors have proposed neural networks for modelling the temperature dependences of elements and parameters of microwave transistor small-signal equivalent circuit including noise, [6]. The neural network used for this purpose has one input neuron corresponding to the ambient temperature. The number of the neurons in the output layer corresponds to the number of transistor equivalent circuit elements and parameters that are temperature dependent ($N$ in Fig.2 and 3). These modelled elements and parameters will be denoted as ECP (*Equivalent Circuit Parameters*). The number of hidden neurons is optimised during the training.

The model development starts from transistor signal and noise data measured at several temperature points. Using these measured values, for each temperature ECP are extracted. One of the circuit-oriented modelling methods can be used for this purpose. Further, the obtained values are used for the training of neural networks with different number of the hidden neurons. The network with the best prediction results is chosen as the model of the ECP temperature dependence. Within a standard microwave simulator, the neural network can be assigned to the transistor equivalent circuit as follows: the math expressions describing the network are generated and put into a VAR (Variable and Equation) block added to the equivalent circuit schematic. This VAR block has the temperature as the input and ECP values as outputs that are assigned to the corresponding ECP. This new schematic can be used as a user-defined library element, with the ambient temperature as the input, Fig 2, enabling the noise parameters' determination at each operating temperature, without need for noise parameters' measured values at that temperature and without any optimisation.

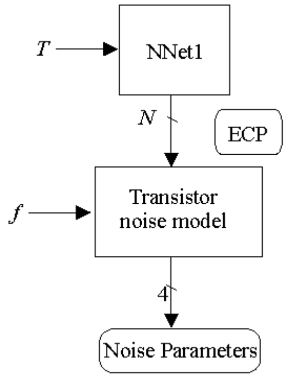


Fig. 2. Transistor noise neural model

The accuracy of the model described above is limited by the accuracy of the chosen transistor noise model and the accuracy of the extraction of the ECP used for the network training. The better ECP extraction is, the better training data are and therefore, the better neural model is. But, although the great accuracy of the ECP extraction can be achieved, the accuracy of the proposed neural model couldn't be better than the accuracy of the original transistor model and this is the main limitation of the proposed neural model. Therefore, the advantage of this neural model is that the temperature dependence is included in the noise model but there are no improvements regarding the model accuracy.

## IV. Improved Neural Noise Model

The model accuracy of the earlier proposed temperature dependent neural model can be increased using an additional neural network aimed to correct values of the noise parameters obtained as described above. These values and the corresponding temperature and frequency are presented to the additional neural network (Nnet2 in Fig. 3) trained to produce more accurate values of noise parameters, Fig 4.

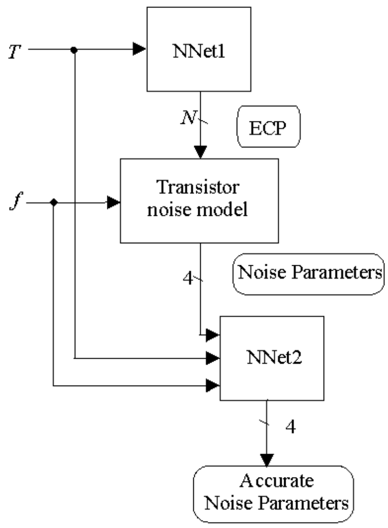


Fig. 3. Improved transistor noise neural model

Therefore, that network has six input neurons corresponding to the ambient temperature, frequency and four computed noise parameters (minimum noise figure, magnitude and angle of optimum reflection coefficient and equivalent noise resistance). In the output layer there are four neurons corresponding to the improved noise parameters. The number of hidden neurons is optimised during the training. The network is trained using a set of the measured noise parameters for a certain number of temperatures and frequencies and corresponding values of the noise parameters obtained by the previously described neural model. Since it is trained using the measured data, once trained, this neural network can be used for noise parameters' correction over the whole operating temperature range. That would enable accurate transistor noise prediction no matter what the accuracy of the chosen transistor noise model is. The correction neural network can be added easily to the earlier proposed user-defined library element by putting the math expressions describing it into a new VAR block on the previous model schematic. The VAR block inputs are the temperature, frequency and noise parameters obtained by the previous neural model. The outputs of the VAR block are values noise parameters that are assigned to the device, forming the final user-defined library element.

## V. MODELLING RESULTS

Both of the proposed models are applied to an HEMT device (NE20283A) in a packaged form, in the temperature range (-40÷60)°C. The measurements of the device noise parameters were performed by a research group with the University of Messina, by using an automated measurement system [7], [8]. The Pospieszalski's model, [9], is used for the transistor noise representation, Fig 4.

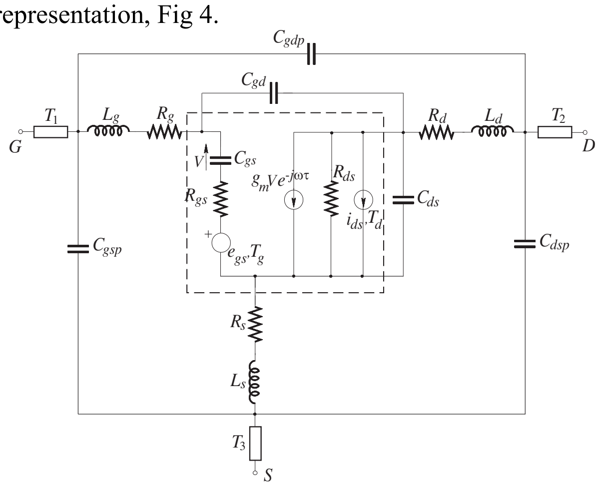


Fig. 4. Pospieszalski's transistor noise model

The intrinsic small-signal equivalent circuit including two noise sources is framed with a broken line. The extrinsic circuit elements represent package effects and parasitic effects. Voltage noise source $e_{gs}$ and current noise source $i_{ds}$ represent the effects of noise generating inside the device. The equivalent temperatures $T_g$ and $T_d$ are assigned to the voltage source $e_{gs}$ and current source $i_{ds}$, respectively. The equivalent temperatures are empirical model parameters and can be obtained by an optimisation process from the measured device noise data. The noise parameters related to the intrinsic circuit can be expressed as functions of equivalent circuit elements, two equivalent temperatures and frequency. Once four noise parameters of intrinsic circuit are determined, other model elements have to be added to the circuit with the aim to determine the noise parameters of the whole packaged device. The temperature of all resistance elements in the extrinsic circuit contributing to the total noise is assumed to be equal to the ambient temperature.

Therefore, the number of the ECP to be modelled is 20: 19 small-signal model elements and the equivalent drain noise temperature $T_d$. The equivalent gate noise temperature $T_g$ is assumed to be equal to the ambient temperature. Firstly, the NNet1 was trained from the extracted values of the ECP at the mentioned temperatures. The network with 5 hidden neurons was chosen as the best. Then, the model was implemented in the ADS simulator, [10]. The noise parameters' values obtained by this new model at the temperatures {-40°C, 0°C, 20°C and 60°C} and the corresponding measured noise parameters, were used for the NNet2 training. The best-obtained NNet2 has 10 hidden neurons. After the model had been implemented in the ADS, the comparison of the noise parameters' prediction was done.

As an illustration, in Fig. 5 there is the minimum noise figure prediction in the frequency range (6-18) GHz. It is obvious that the values obtained by the improved neural model (solid line) are closer to the reference (measured) values (circles) then the ones obtained by the neural model without correction (doted line). The modelling accuracy improvement is achieved not only at the training temperatures but also at the temperatures {-20°C and 40°C} not used for the training. This improvement at the temperatures not used for the training is more obvious in Fig. 6., where the magnitude of optimum reflection coefficient is shown. In Figs. 7 and 8 there is the temperature dependence (step 1°C) of the magnitude of optimum reflection coefficient determined by neural models without (Fig. 7.) and with (Fig.8.) correction. The effects of the correction are most obvious at the boundaries of the temperature range.

## VI. CONCLUSION

On the basis of the numerical results analysis, it can be concluded that the accuracy of the earlier proposed temperature dependent neural model could be increased by using an additional neural network. The network is aimed to correct values of the noise parameters. The measured noise parameters are required only for training of the networks. After the model development, i.e. after the networks' training, for any temperature from the operating temperature range, the noise parameters can be determined accurately without knowledge about the noise parameters' measured values. The proposed neural model can be implemented very easily into standard microwave simulators. Therefore a new user defined library element, that represents the temperature dependent transistor model including noise, can be created. This would make temperature dependent noise analyses much faster and very efficient.

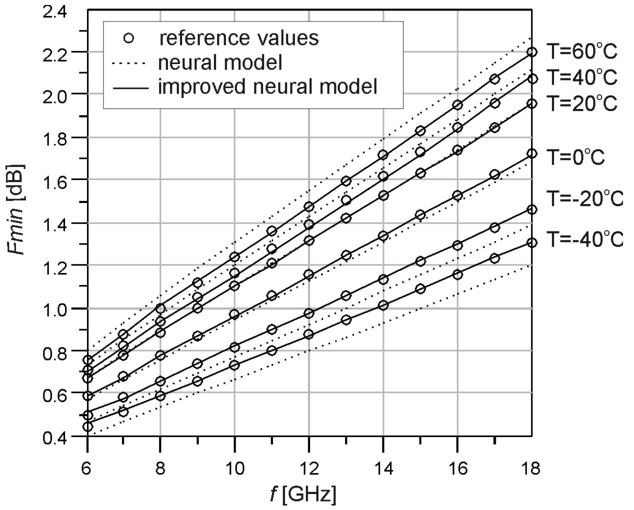


Fig. 5. Minimum noise figure

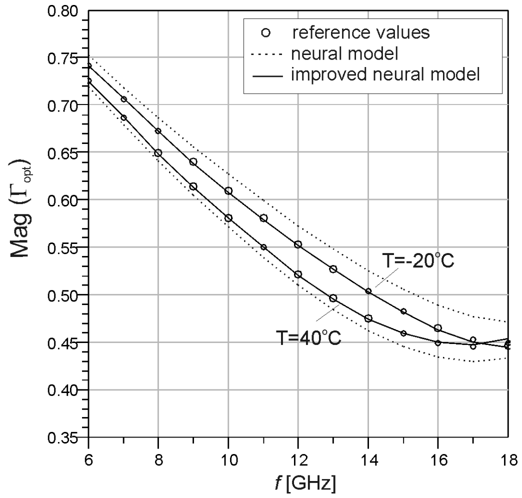


Fig. 6. Magnitude of optimum reflection coefficient – temperature not used for Nnet2 training

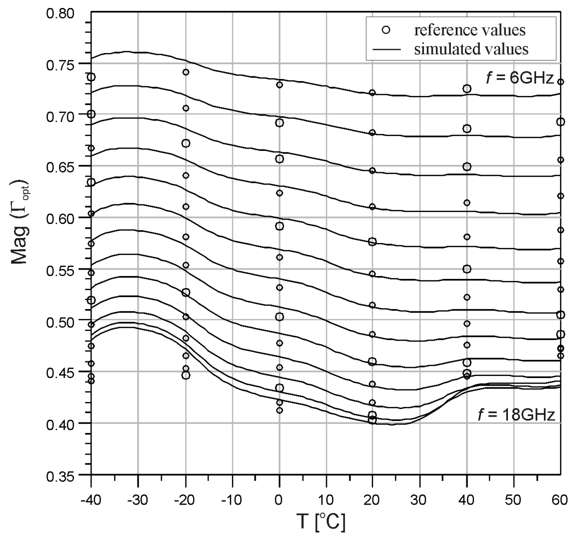


Fig. 7. Magnitude of optimum reflection coefficient – neural model without correction

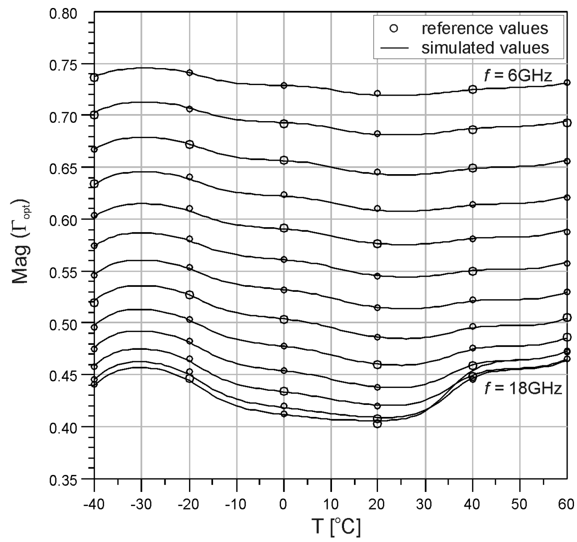


Fig. 8. Magnitude of optimum reflection coefficient – neural model with correction (improved neural model)


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