Comparison of Temperature Dependent Noise Models of Microwave FETs

Zlatica D. Marinković, Vera V. Marković and Olivera R. Pronić

Abstract – **In this paper, a comparison of hybrid empirical-neural noise models of microwave FET transistors earlier-proposed by the authors is done. The models are compared from various aspects such as: model accuracy, model complexity, a number of measured data needed for a model development, etc. Moreover, the models are contrasted to the models based on neural networks only.**

Keywords – **Neural networks, microwave FET, noise.**

I. Introduction

During the last decade, neural networks have found many applications in modelling in the microwave area, [1]-[7]. 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. 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. They have been applied in microwave FET transistor signal and noise performance modelling as well, [3]-[7].

Accurate and reliable noise models of microwave transistors are required 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 temperature, but most of the existing transistor signal, and especially noise models refer to a single temperature (usually, nominal temperature). Therefore, for further analyses involving various temperature conditions, it is necessary to develop models for each operating temperature point. Model development is basically an optimisation process, usually time-consuming. Furthermore, measured signal and noise data for each new operating point are necessary for model development. Since these measurements require complex equipment and procedures, measured data acquiring could take much effort and time.

Applying neural networks in the noise modeling can make modeling procedures more efficient and more accurate. Authors of this paper have proposed several temperature-dependent noise models of microwave transistors based on the neural networks. On the one side, there are hybrid-empirical models where neural networks are used for including the temperature dependence into an existing empirical device noise model, [5]-[7]. On the other side, there are black-box models based on neural networks only, [5]. In this paper a detailed comparison of the proposed hybrid empirical-neural noise models is done. The models are compared from various aspects: model accuracy, model complexity, a number of measured data needed for a model development, etc. Furthermore, the models are contrasted to the models based on neural networks only. Additionally, several recommendations regarding applicability of the models and their development are given.

The paper is organized as follows: after Introduction, In Section II neural networks are shortly described. A brief review of the proposed neural models is given in Section III. Modelling example is presented in Section IV. Finally, in Section VI the main conclusions are reported.

II. MLP Neural Network

A multilyer perceptron neural network (MLP), such has been used in this work, consists of neurons grouped into layers: one input layer, several hidden layers and one output layer, [1]. The network inputs are inputs of the first layer neurons. 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. The network outputs are outputs of the output layer neurons. 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.

The neural network learns relationship among sets of input-output data (training set) by adjusting the 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.

For all networks trained for the purpose of work, a number of the hidden neurons was determined during the network training process. For each network structure, neural networks with different number of the hidden neurons were trained and the modelling ability of each network was tested. The network with the best modelling results was chosen as the model of the considered structure.

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III. Transistor Noise Models Based on Neural Networks

A microwave transistor, as a 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. Noise characteristics of the device are usually treated in terms of four noise parameters: minimum noise figure $F_{\min}$, equivalent noise resistance R_n, and magnitude and angle of the optimum reflection coefficient, corresponding to the generator impedance resulting in minimum noise figure, $Mag(\Gamma_{opt})$ and $Ang(\Gamma_{opt})$.

In the text below, the proposed microwave transistor noise models based on neural networks are described. The first proposed model, a basic hybrid empirical-neural model, framed with a dotted line in Fig 1, consists of an existing empirical device noise model based on equivalent circuit representation and a neural network (NNet1) trained to model temperature dependence of equivalent circuit elements and parameters, (ECP), [5]. This network has one input neuron corresponding to the ambient temperature. The number of the neurons in the output layer corresponds to the number of transistor ECP (*N* in Fig. 1). The number of hidden neurons is optimised during the training.

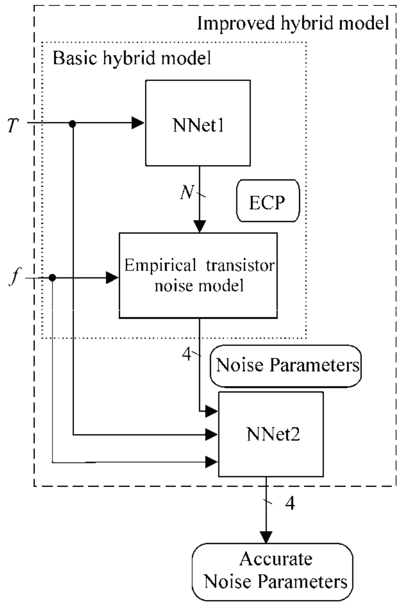

Fig. 1. Hybrid empirical-neural noise models

The model development starts from transistor signal and noise data measured at several temperature points. Using these measured values, ECP are extracted for each temperature. Further, the network training is done, and the trained network is assigned to the earlier-implemented device empirical model within a standard microwave simulator. The new model can be used as a user-defined library element, with the ambient temperature as the input, enabling the noise parameters' determination at each operating temperature, without need for noise parameters' measured values at that temperature and without additional optimizations.

A drawback of the basic hybrid empirical-neural model is that its accuarancy can not be greater than the accuracy of the empirical model itself. Therefore, an alternative solution for improvement of the hybrid model enabling accuracy has been proposed in [7].

The mentioned improvement of the basic hybrid model is based on adding an additional neural network (NNet2) aimed to correct values of the noise parameters obtained by the basic hybrid model, Fig. 1. The inputs of the NNet2 network are temperature and frequency and the corresponding values obtained by the basic hybrid model. The training process of the NNet2 requires the basic hybrid model to be implemented previously, in order to obtain approximate values of the noise parameters for all combinations of the temperature and frequency used for the training. Since the measured values of the noise parameters are used as target output values for the NNet2, accuracy greater than the accuracy of the basic hybrid model can be achieved.

On the other hand, there is a black-box model, Fig 2, [5], consisting of a single neural network with two inputs corresponding to the temperature and frequency and four output neurons corresponding to the four noise parameters. The network is trained using the measured values of the noise parameters.

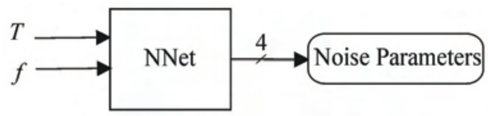

Fig. 2. Black-box neural noise model

IV. Modeling Example

The above described models were applied to an HEMT device (type 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 [8], [9]. The Pospieszalski's model, [10], is used for the transistor noise representation, Fig 3.

The intrinsic small-signal equivalent, framed with a broken line, includes two noise sources. The extrinsic circuit elements

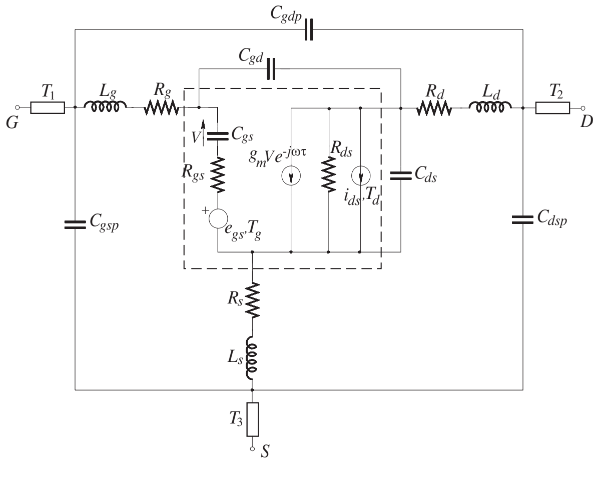

Fig. 3. Pospieszalski's transistor noise model

represent package effects and parasitic effects. Voltage noise source e_{gs} and current noise source i_{ds} represent the noise generated 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 are extracted from the measured device noise data through an optimisation process. The noise parameters related to the intrinsic circuit can be expressed as functions of equivalent circuit elements, two equivalent temperatures and frequency, [10]. 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 noise temperature of all resistances in the extrinsic circuit 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 for the mentioned temperatures. The network with 5 hidden neurons was chosen as the best, [5]. Then, the model was implemented in the ADS simulator, [11]. The noise parameters' values obtained by this new model at the temperatures: -40°C, 0°C, 20°C and 60°C and together with the corresponding measured noise parameters, were used for the NNet2 training. The best-obtained NNet2 has 10 hidden neurons, [7].

As an illustration, in Fig. 4 there is plot of the magnitude of optimum reflection coefficient in the frequency range (6-18) GHz. It is obvious that the values obtained by the improved hybrid model (solid line) are much closer to the reference (measured) values (squares) then the ones obtained by the basic hybrid model (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 network training. The effects of the improvement are the most obvious at the boundaries of the temperature range.

The black-box neural noise model was developed using all of the available data, since training of the networks with a reduced set of the measured data did not give satisfactory modelling accuracy. The best-obtained NNet has two hidden layers each having 10 neurons. Compared to the basic hybrid model, this model provides better modelling accuracy, as can be confirmed by the scattering plots given in Figs. 5 and 6, showing the values of the magnitude of the optimum reflection coefficient versus the corresponding measured values for both of the models. There is less scattering from the ideal diagonal line $y=x$ in the case of the black-box neural modelling. On the other hand, the modelling accuracy of the black-box neural modelling is similar to the accuracy of the improved hybrid model, which can be observed by contrasting the corresponding scattering plots given in Figs. 6 and 7. As a further confirmation of the above-stated, in Fig. 8. there are values of the magnitude of the optimum reflection coefficient obtained by the black-box model (circles) matching very well to the corresponding ones obtained by the improved hybrid model (crosses).

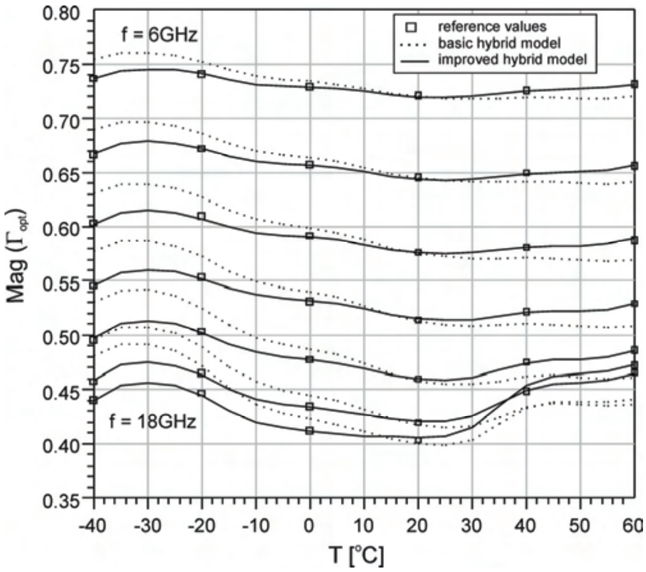

Fig. 4. Magnitude of optimum reflection coefficient

V. Conclusion

All of the proposed models, the hybrid empirical-neural ones and the black-box one, provide efficient noise modelling of microwave FET transistors. Contrary to the most of existing empirical models, where model development should be repeated for each operating temperature, once a neural model is developed, it is valid in the whole operating frequency and temperature range.

The advantage of the basic hybrid empirical-neural model is that the temperature dependence is included in the noise model but there are no improvements regarding the modelling accuracy.

Modelling accuracy can be enhanced by the improved hybrid empirical-neural model, which has an additional neural network aimed to correct values of the noise parameters. Since the correction network is trained using the measured noise data, the achieved modelling accuracy can be equal to the accuracy of the measured data. The previous is valid for the accuracy of the black-box neural model as well. In the both cases, all mechanisms of generating noise are included in the model.

The improved hybrid model has at its inputs additional knowledge about the noise parameters. Therefore, it requires less training data than the black box model and is suitable when there are no enough training data.

On the other hand, regarding the time needed for a model development and a number of necessary optimizations, the black-box model is the most efficient, since only the training of one neural network should be done and there are no optimizations in a circuit simulator. Hence, it is the best solution if there are enough measured data for the model development.

All of the proposed models can be easily implemented in standard microwave simulators.

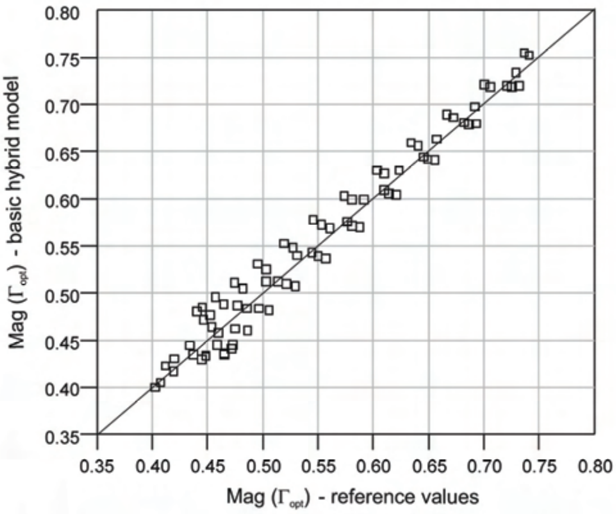

Fig. 5. Magnitude of optimum reflection coefficient
Scatering plot: basic hybrid model vs. reference data

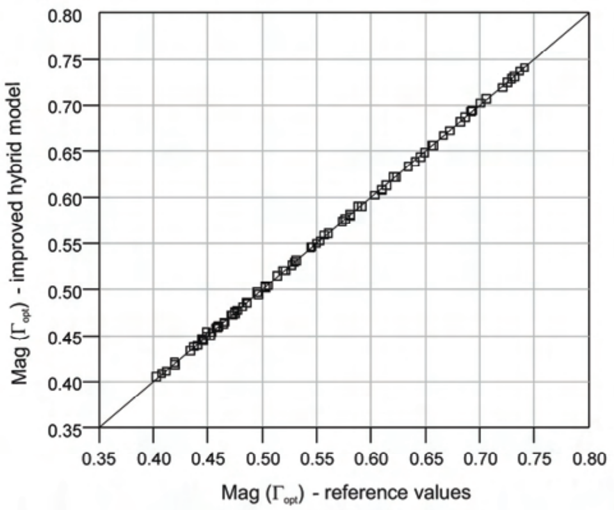

Fig. 6. Magnitude of optimum reflection coefficient
Scatering plot: improved hybrid model vs. reference data

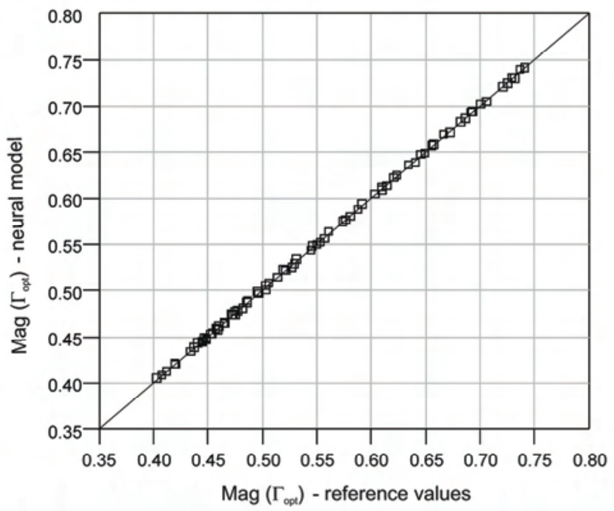

Fig. 7. Magnitude of optimum reflection coefficient
Scatering plot: black-box neural model vs. reference data

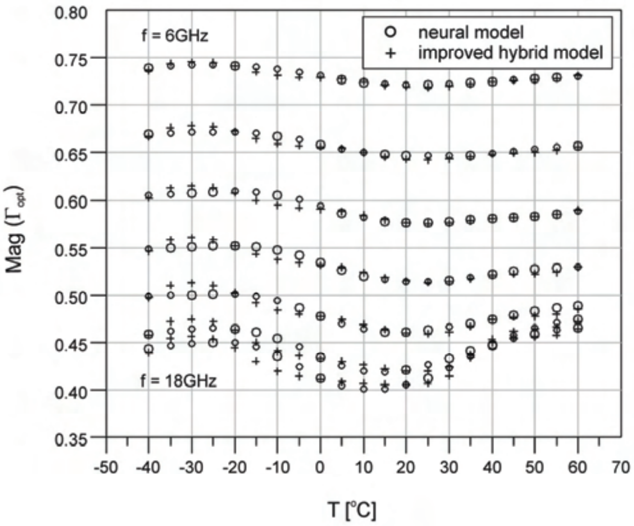

Fig. 8. Magnitude of optimum reflection coefficient
Improved hybrid model contrasted to black-box model

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