# New Neural Procedure for Extraction of Parameters of Microwave FET Noise Models

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***Abstract* — A neural netwok based procedure for extraction of parameters of microwave FET noise models is proposed in this paper. The procedure is illustrated on the Pospieszalski's noise model. A neural network is trained to predict the equivalent drain noise temperature for given values of the intrinsic circuit elements, intrinsic noise parameters, ambient temperature and frequency. In this way, the repeated extraction procedures in microwave circuit simulators are avoided. The presented approach is validated on a specific HEMT device noise modeling. The results are compared with the results obtained for the model parameters extracted by using the standard optimization based extraction procedures.**

***Keywords* — Artifcial neural networks, equivalent noise temperatures, HEMT, MESFET, noise model.**

## I. Introduction

LOW noise microwave FETs (MESFETs, HEMTs) are very important parts of active circuits in modern communication systems. Hence, their small-signal and noise modeling requires special care in the computer-aided design of active circuits.

When operating under small-signal conditions, microwave FETs can be described by four complex small-signal scattering (S-) parameters. Noise characteristics of a device are usually treated in terms of four noise parameters: minimum noise figure, $F_{min}$, magnitude and phase of complex optimum source reflection coefficient, $\Gamma_{opt}$, and normalized noise resistance, $r_n$. The S and noise parameters are frequency-, temperature- and bias-dependent. Since measurements of S-, and especially, noise parameters include complex and time-consuming procedures, using of device models is a common way for prediction of the signal and noise performance in the microwave circuit design, [1]-[6]. The physical transistor models are complex and require many input technological parameters [1]-[2]. Therefore the empirical models, mostly based on equivalent circuit representations, are usually used for device signal and noise prediction in the microwave circuit design, [3]–[6].

The two-parameter Pospieszalski's noise model [5] is considered to be the most suitable one for implementation into the standard commercial microwave circuit simulators. The Pospieszalski's noise model is based on simple expressions for the noise parameters of MESFET/HEMT intrinsic circuit as functions of the noise equivalent circuit parameters (ECP): transistor intrinsic circuit elements and equivalent gate and drain noise temperatures. The ECPs are extracted by optimization procedures from measured S- and noise parameters.

Most of the transistor noise models, including [5], are valid only for a single operating point (bias and temperature). Namely, it is necessary to repeat extraction of ECPs for each operating point, which can be very time-consuming. Moreover, each new extraction requires new measured data. To avoid repeating optimizations of model parameters, extractions based on the artificial neural networks (ANN) can be used, as shown in this paper.

ANNs have found applications in different modeling problems in the field of microwaves, and especially in modeling of microwave transistors [7]-[20]. ANNs are very convenient as a modeling tool, since they have the capability of approximating any nonlinear function and the ability to learn from experimental data. Therefore, a neural model can be developed from source-response data points without the knowledge about the physical characteristics of the problem to be modeled. The most important feature of neural models is their generalization capability i.e. the capability of providing a correct response even for the input values not presented in the training process. In that way, the developed models can be used for a reliable prediction over a wide range of input parameters. It should be noted that once developed neural models give responses almost instantaneously, because response providing is based on performing basic mathematical operations and calculating elementary mathematical functions.

In this paper an ANN based procedure for extraction of parameters of microwave FET noise model [5] is proposed. Namely, a neural network is trained to predict equivalent drain noise temperature for given equivalent intrinsic circuit elements, intrinsic circuit noise parameters, ambient temperature and frequency. In this way, by using the suggested procedure, optimization procedures in microwave circuit simulator can be replaced by simple calculation of the ANN response. The proposed approach is validated by comparison of the noise parameters calculated by using the equivalent drain noise

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temperature extracted by the proposed approach with the reference ones calculated by using the equivalent drain noise temperature extracted by optimizations.

The paper is organized as follows: The empirical Pospieszalski's noise model [5] is briefly described in Section II. Earlier proposed neural procedures for ECP extraction are analyzed in Section III. The proposed procedure for equivalent drain temperature extraction is described in Section IV. A modeling example and the main numerical results are presented in Section V. Finally, in Section VI the main conclusions are reported.

## II. Pospieszalski's Transistor Noise Model

During the last two decades, the empirical transistor noise model of MESFETs/HEMTs proposed by Pospieszalski [5] has been widely considered as one of the most convenient and accurate for a single operating point (bias / temperature). In Fig.1 a small-signal and noise model for package MESFETs/HEMTs, based on this approach, is shown. The intrinsic equivalent circuit including two noise sources is framed with a broken line. The extrinsic circuit elements represent the effects of package and parasitic effects.

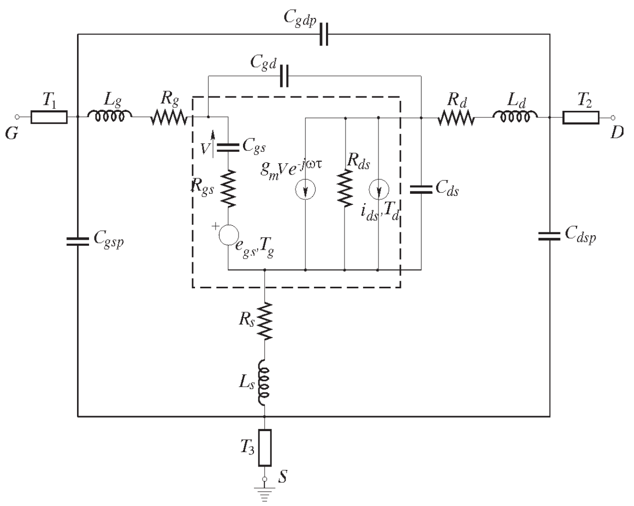


Fig 1. Microwave FETs equivalent circuit including noise sources.

Voltage noise source, $e_{gs}$, and current noise source, $i_{ds}$, represent the effects of noise generating inside the device. The equivalent temperatures: $T_g$ - gate noise temperature and $T_d$ - drain noise temperature are assigned to the voltage and current noise source, respectively. These equivalent temperatures are empirical model parameters that can be obtained by an optimization process from measured component noise data.

The noise parameters related to the intrinsic circuit can be expressed as functions of equivalent circuit elements, two equivalent noise temperatures and frequency as follows:

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

$$T_{\min} = 2\frac{\omega C_{gs}}{g_m}\sqrt{\frac{R_{gs}T_gT_d}{R_{ds}}+\left(\frac{\omega C_{gs}R_{gs}T_d}{g_mR_{ds}}\right)^2 +\left(2\frac{\omega C_{gs}}{g_m}\right)^2\frac{R_{gs}}{R_{ds}}T_d}, \tag{2}$$

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

$$\Gamma_{opt,\mathrm{int}} = \frac{Z_{opt}-Z_0}{Z_{opt}+Z_0}, \tag{4}$$

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

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

where $T_0$=290K is the reference noise temperature and $Z_0 = 50\Omega$. $T_{\min}$ is the minimum noise temperature and $Z_{opt} = R_{opt} + jX_{opt}$ is the optimum generator impedance.

Once noise parameters of the intrinsic circuit are determined, the transistor model extrinsic 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 resistive elements in the extrinsic circuit contributing to total noise is assumed to be equal to the ambient temperature.

It is shown [5] that the gate noise temperature is approximately equal to the ambient temperature ($T_g = T_a$), therefore Pospieszalski's model can be considered as one-parameter noise model.

## III. Neural Procedures for ECP Extraction

The small-signal ECPs are extracted from the measured scattering parameters in the operating frequency range. Usually extraction procedure is an optimization in a microwave circuit simulator. The equivalent noise temperatures are optimized in order to have the model simulating the noise parameters which match closely the measured noise parameters. As mentioned in the introduction, as the noise and scattering parameters are bias and temperature dependent, for any new operating point it is necessary to repeat extraction procedures.

To avoid repeated extraction procedures, ANNs have been proposed as an alternative extraction tool [9], [13], [15], [19], [20]. In all mentioned cases, standard multilayered ANNs are used [7].

The first approach is based on an ANN trained to model the dependence of the ECPs on the operating conditions, as shown in Fig. 2 [13], [15]. The ANN has as many inputs as the number of parameters describing considered operation conditions (*n*). The number of output neurons is equal to the total number of ECPs, which is the sum of the number of small-signal model ECPs (*N*) and the number of ECPs describing noise; in this case there is only one parameter describing noise - equivalent drain noise temperature $T_d$. For building the ANN training set it is necessary to extract ECPs from the measured S and noise parameters in a standard extraction way for a certain number of different operating points. Once the ANN is trained, the ECPs referring to a particular operating point are simply determined by calculation of the ANN outputs.

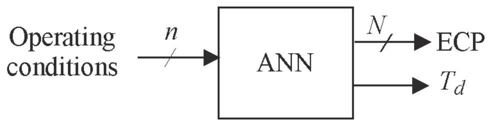


Fig. 2. ANN model of ECP dependence on operating conditions.

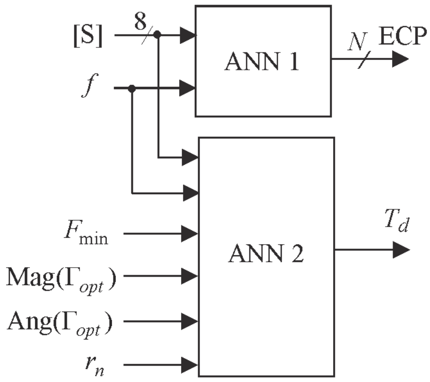


Fig. 3. Transistor noise model ECP extraction by using neural networks.

According to the second approach, ANNs are used for determination of the ECPs directly from the measured transistor characteristics [9], [19], [20]. Namely, there are two ANNs developed for this purpose, as shown in Fig. 2. Since the transistor small-signal ECPs are extracted from the measured S-parameters, one ANN (ANN 1 in Fig. 2) is trained to model the dependence of *N* small-signal ECPs on the S-parameters [9], [20]. Having in mind that the S-parameters are frequency-dependent, the frequency is chosen as one of the ANN inputs. Therefore, this ANN has 9 input neurons, 8 corresponding to the real and imaginary parts of the four complex S-parameters and one corresponding to frequency. The ANN 1 has *N* output neurons, which is 19 in the case of the small-signal model shown in Fig 2. The ECPs representing noise effects of the model are extracted from both scattering and noise characteristics. Therefore, the ANN trained to extract these ECPs has noise characteristics as inputs, in addition to S-parameters and frequency. In this work it is assumed that the noise characteristics are described by four noise parameters (minimum noise figure, magnitude and angle of optimum reflection coefficient and equivalent noise resistance) [19]. Therefore, the network ANN 2 has 13 inputs in total. The number of outputs is equal to the number of ECPs introducing noise effects in the equivalent circuit. As mentioned above, in this particular case this number is one as there is only one noise model parameter - equivalent drain noise temperature, $T_d$ .

The ECP values used for the ANN1 and ANN 2 training are extracted in the standard way from a certain number of measured S- and noise parameters. Once the training is done, the ECPs are determined directly by calculating the responses of the ANN 1 and ANN 2 for the given set of the S- and noise parameters.

As mentioned in [19], where two described models are compared in detail, for both approaches, the accuracy of the extraction of ECPs which are used for training of ANNs influences the accuracy of the further ANN based extractions of ECPs. In order to avoid this influence, here a new approach to the development of an ANN for extraction of parameters is proposed. It should be mentioned that only the ANN aimed for equivalent drain noise temperature is considered. Improvements of the ANN based extraction of small-signal ECPs will be a part of further work.

## IV. Proposed Equivalent Noise Temperature Extraction Procedure

The proposed approach is shown in Fig. 4. As mentioned above, only improvements of the ANN related to the equivalent drain noise temperature are considered at this moment. As far as the ECP extraction of the small-signal model is considered, it is the same as in the second approach described in the previous section. It should be noted that in Fig. 4, instead of *N* outputs corresponding to the small-signal ECPs, the $N_1$ extrinsic and $N_2$ intrinsic ECPs are shown separately ( $N = N_1 + N_2$ ).

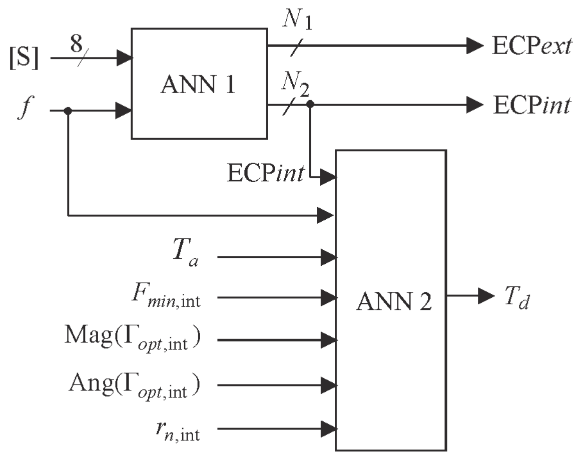


Fig. 4. Transistor noise model ECP extraction by using neural networks - proposed approach.

In the standard extraction procedure the equivalent drain noise temperature is obtained by optimization for the given small signal ECPs in order to achieve modeling of the intrinsic circuit noise parameters as accurate as possible. Therefore, the optimization procedure has as the inputs: the intrinsic circuit small-signal elements, equivalent gate noise temperature, $T_g$ (which is equal to the ambient temperature $T_a$), frequency and intrinsic circuit noise parameters.

The proposed ANN based neural approach is based on an ANN trained to determine directly $T_d$ for the given inputs. In other words, this ANN should be an inverse function of the function for determination of the intrinsic noise parameters based on the expressions (1) - (6). Therefore, the ANN, shown in detail in Fig. 5, has ten inputs corresponding to: four intrinsic circuit elements (gate-to-source capacitance, $C_{gs}$ , gate-to-source resistance, $R_{gs}$, transconductance magnitude, $g_m$, and drain-to-source resistance $R_{ds}$), ambient temperature, $T_a$, frequency, $f$, and four intrinsic noise parameters. There is only one output corresponding to $T_d$.

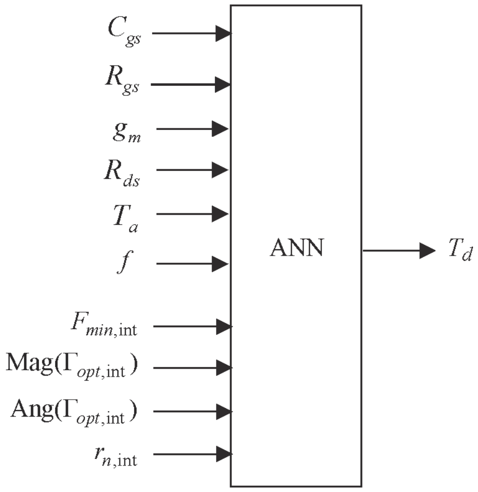


Fig. 5. Proposed ANN for $T_d$ extraction.

Having in mind that this ANN is an inverse function of the expressions (1) - (6), the datasets for the ANN training and validation are obtained by using the mentioned expressions. Namely, for a certain number of combinations of intrinsic circuit elements, ambient temperature, $T_d$ and frequency, the noise parameters are calculated by using the expressions (1) - (6), and then the training and test datasets are formed. Once the ANN has been trained, the noise temperature $T_d$ is determined by a simple calculation of the ANN output.

## V. Numerical Results

The ANN training and test datasets were created by using randomly sampled values of the equivalent circuit elements, ambient temperature and frequency. The training set consisted of 9000 samples and the test set consisted of 1000 samples. The chosen ranges of values were based on the typical equivalent circuit elements and $T_d$ values for a HEMT device working in the temperature range from 233K to 333K and in the frequency range from 6 to 18 GHz. The corresponding ANN input noise parameters were calculated by using expressions (1) - (6).

Since the number of hidden neurons is not a priori known, several ANNs with different number of neurons were trained and the ANN showing the best prediction and generalization performance was chosen as the final ANN to be used for $T_d$ extraction. It has one hidden layer containing 5 neurons. The Levenberg-Marquardt training algorithm was used [7].

To test the ANN extraction abilities, for temperatures from 233 K to 333 K (20 K step), small-signal intrinsic ECPs as well as $T_d$ for a NE20283A device (by NEC) were taken from [21]. The intrinsic circuit noise parameters were calculated from (1) - (6) for the frequencies from 6 to 18 GHz (0.1 GHz step). Then, for each ambient temperature, $T_d$ was calculated by using the developed ANN. It was found that the extracted $T_d$ values are very close to the ones used for calculating the ANN input noise parameters. The prediction errors are less than 1% in all cases. As can be seen from Fig. 6, the extracted values are almost constant versus frequency.

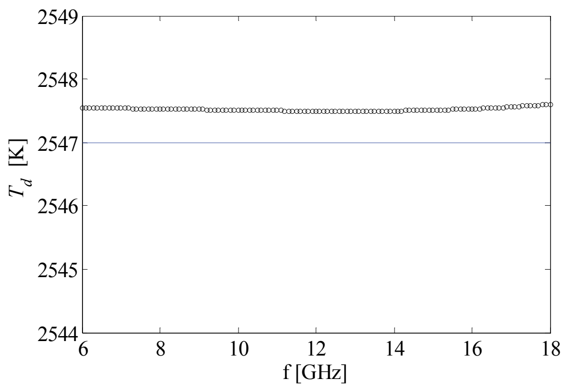


Fig. 6. ANN extracted $T_d$ (symbols) compared to the target (line) at 293 K.

The next step in the approach validation was comparison of the noise parameters calculated by using the extracted $T_d$ and the reference noise parameters calculated by using the reference $T_d$. As the temperature $T_d$ slightly differs with the frequency change, in calculations for each mentioned ambient temperature $T_d$ averaged over frequency range was used. A very good agreement of the calculated and reference noise parameters was obtained. As an illustration, Fig. 7 shows the intrinsic noise parameters at the 293K ambient temperature. Similar results are obtained for other ambient temperatures.

## VI. Conclusion

A new, ANN based procedure for extraction of the parameters of a microwave FET noise model is proposed in this paper. Namely, the considered Pospieszalski's noise model is valid only for a single temperature/bias operating point, therefore for each new operating point it is necessary to repeat extraction of ECPs, which can be very time-consuming. In order to avoid repeated extraction procedures, extractions based on the artificial neural networks can be used.

Since the accuracy of the extraction of ECPs which are used for training of ANNs influences the accuracy of the further ANN based extractions of ECPs, a new approach in development of an ANN for extraction of parameters is proposed in this paper. Here, only the ANN aimed for noise model parameters extraction is considered and the improvements of the ANN based extraction of small-signal ECPs will be a part of further work.

A neural network is trained to predict equivalent drain noise temperature for given equivalent intrinsic circuit elements, intrinsic circuit noise parameters, ambient temperature and frequency. In this way, extraction of the equivalent drain noise temperature became more efficient, as optimization procedures in microwave circuit simulator are avoided.

The accuracy of the proposed extraction approach is validated for a specific HEMT device working under different temperature conditions. Validation was done by comparison of the noise parameters calculated by using the ANN extracted drain temperature with the reference ones obtained by using the equivalent drain noise temperature extracted in a standard optimization procedure in a microwave simulator. Good accuracy was achieved for all considered ambient temperatures.

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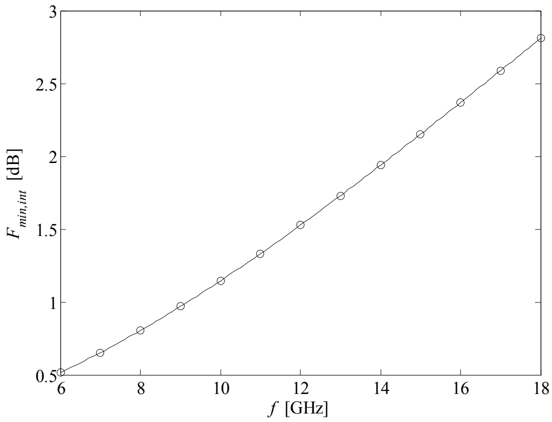
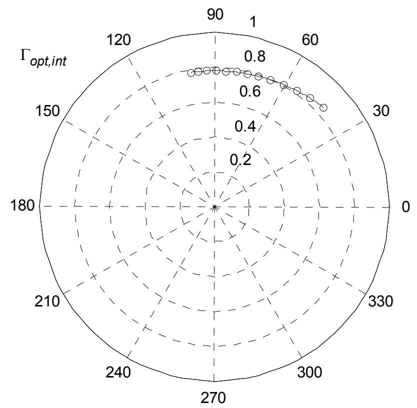



(a)

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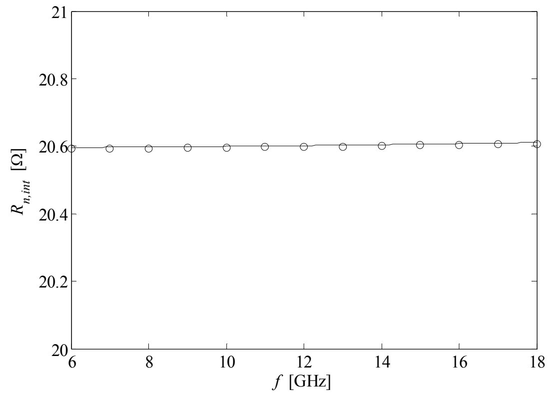


(c)

Fig. 7. Intrinsic noise parameters (symbols - refer to reference $T_d$ values, lines - refer to ANN extracted $T_d$ ) (a) minimum noise figure; (b) optimum reflection coefficient; (c) equivalent noise resistance.