Application of Adaptive Neuro-Fuzzy Inference System for Predictaion of HEMT Transistor Noise Parameters

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***Abstract*—In this paper, simulation of HEMT Transistor Noise Parameters such as minimum noise figure, normalized equivalent resistance , magnitude of optimum reflection coefficient and angle of optimum reflection coefficient dependence on bias conditions such as dc drain-to-source voltage, dc drain-to-source current, frequency and S-parameters using ANFIS model is carried out. This model can accurately predict transistor noise parameters in a wide frequency ranges for all bias points from the operating range including transistor S-parameters. The proposed models can be used as efficient tools for noise modeling of HEMT transistor.**

***Index Terms*—HEMT transistor, adaptive neuro-fuzzy inference system, high electron mobility transistor, s-parameter, noise modeling.**

I. Introduction

Microwave noise characteristics of high electron mobility transistors (HEMT) are very important for microwave applications of these devices. Noise characteristics of a transistor can be characterized by a noise figure F, expressed as [1, 2]

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

where $F_{\min}$ is a minimum noise figure, R_n is an equivalent noise resistance, Γ_{opt} is the optimum reflection coefficient, and finally, z_o is normalizing impedance. The optimum reflection coefficient refers to the optimum source impedance that results in minimum noise figure, $F=F_{\min}$. The noise parameters $F_{\min}$, Γ_{opt} and R_n describe inherent behavior of the component and are dependent on bias conditions and frequency circuit. The microwave active circuits that are parts of modern communication systems, it is very important to keep the noise at a low level. Model development is basically an optimization 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 [1]. The noise model by Pucel et al [3] and by Pospieszalski [4], [5] is the most popular among equivalent circuit noise models. These models are quite helpful in understanding the noise sources inside the transistor, which contribute to the low-noise amplifier circuit design. Neural modeling could be a good alternative to the classical modeling. Neural models are simpler and retain the similar accuracy. They require less time for providing response, therefore, application of neural model can make simulation and optimization processes less time-consuming, shifting much computation from on-line optimization to off-line training. Neural networks have been applied in modeling of either active devices or passive components, in microwave circuit analysis and design, etc. It has been proposed in microwave, MESFET and HEMT transistor signal and noise performance modeling [6]-[8]. In this paper, Adaptive Neuro-fuzzy inference System (ANFIS) for HEMT transistor noise modeling is proposed. This network receives bias such as dc drain-to-source voltage, dc drain-to-source current, frequency and S-parameters as inputs and produces transistor noise parameters at its output.

Therefore, bias conditions and frequency are inputs and minimum noise figures, magnitude of optimum reflection coefficient, angle of optimum reflection coefficient and normalized equivalent noise resistance are outputs of the neural networks. A simplified overview of proposed model is shown in Fig. 1

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II. Adaptive Neuro-Fuzzy Inference System

Neural networks have been applied in the microwave area. There are some neural models that refer to the microwave transistors [7], [8].

MLP networks are applied with the aim to model the microwave transistor noise parameters dependence on frequency and bias conditions [9], [10].

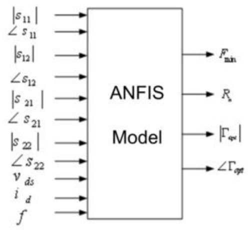

Fig. 1. A simplified overview of the model.

In this paper, Adaptive Neuro-fuzzy inference System for HEMT transistor noise modeling is proposed. This fuzzy neural network incorporates both neural network and fuzzy mathematics.

A neural network is a computational network that has special characteristics such as learning, adaptation, and

Manuscript received July 22, 2012; revised August 25, 2012.

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generalization and fuzzy mathematics has the capacity for processing the approximate reasoning and knowledge based information by using fuzzy logic operations.

Fuzzy logic principles have been used in the fuzzy knowledge-based system is fuzzy IF-THEN rules and membership degrees to the variables [11], [12].

The modeling approach used by ANFIS is Sugeno, or Takagi-Sugeno-Kang, method of fuzzy inference [13], [14]. A typical rule in a Sugeno fuzzy model has the form:
If input 1 = x and input 2 = y, then Output is
f= ax + by + c

The output level f_i of each rule is weighted by the firing strength w_i of the rule. For example, for an AND rule with input 1 = x and input 2 = y, the firing strength is: w_i = And Method ($\mu_1(x)$, $\mu_2(y)$) or $w_i=\mu_{1i}(x).\ \mu_{2i}(y)$ where $\mu_1(x)$, $\mu_2(y)$ are the membership functions for input 1 and input 2 respectively, where i is the membership grade of a fuzzy in layer l.

An example of a membership function is the Gaussian function given by:

$$\mu_1(x) = \exp\left(\frac{-0.5(x-c)^2}{\sigma^2}\right) \tag{2}$$

The final output of the system is:

$$fout = \frac{\sum_{i=1}^{N} w_i f_i}{\sum_{i=1}^{N} w_i} \tag{3}$$

In the ANFIS training algorithm, each epoch is composed of a forward pass and backward pass. In the forward pass, the consequent parameters are identified by the least squares estimate, and in the backward pass the premise parameters are updated by the gradient descent. The following updating formulations can be obtained by:

$$w_{il}(k+1) = sat\left(w_{il}(k) + \Delta w_{il}(k)\right) \tag{4}$$

$$w_{jq}(k+1) = sat\left(w_{jq}(k) + \Delta w_{jq}(k)\right) \tag{5}$$

$$\Delta w_{il} = -\eta_1 \frac{\partial E}{\partial w_{il}} \tag{6}$$

$$\Delta w_{jq} = -\eta_2 \frac{\partial E}{\partial w_{jq}} \tag{7}$$

$$sat(x) = \begin{cases} 1, & if \quad x\rangle 1 \\ x, & if \quad 0 \le x \le 1 \\ 0, & if \quad x\langle 0 \end{cases} \tag{8}$$

where η_1 and η_2 are the learning rates associated with the weights in the hidden layer and output layer, w_{il} and w_{jq} are the weights in the hidden layer and output layer and E sum squares error.

III. Simulation Results

In this section, the noise modeling of *Hewlett Packard's* PHEMT ATF-36163 will be presented. The modeling is done in the frequency range (0.5-18) GHz.

The noise parameters values used for the training data are taken from advanced design system (ADS) software. Test and training samples must be different and are selected randomly from the original database (ADS). The training set was obtained by selecting 216 samples.

We used our database for training the ANFIS models with MATLAB 7.5.0 program. In order to check the generalization capability, a test set containing 45 remained samples was used.

The basic structure of the type of fuzzy inference system seen is a model that maps input characteristics to input membership functions, input membership function to rules, rules to a set of output characteristics, output characteristics to output membership functions, and the output membership function to a single-valued output or a decision associated with the output.

The ANFIS models architecture being used for noise parameters such as minimum noise figure $F_{\min}$ is shown in Table 1, normalized equivalent resistance R_n is shown in Table 2, magnitude of optimum reflection coefficient is shown in Table 3, and model architecture being used for noise parameter such as angle of optimum reflection coefficient $\angle\Gamma_{opt}$ is shown in Table 4.

In order to compare the accuracy of the models, the maximum, minimum and mean relative error for proposed ANFIS models was calculated.

Table 5 shows the ANFIS model results for testing data, where the relative error for variable X is evaluated as

$$\mathrm{RE\%} = 100 \times \frac{\mathrm{X_{(sim)}} - \mathrm{X_{(pred)}}}{\mathrm{X_{(sim)}}} \tag{9}$$

where 'sim' and 'pred' stand for ADS simulation (exact values) and predicted values, respectively. Also, the Mean Relative Error is evaluated as:

$$\mathrm{MRE\%} = \frac{1}{\mathrm{N_P}} \sum_{i=1}^{\mathrm{N_P}} \left|\mathrm{RE\%}\right|_i \tag{10}$$

where N_P is the number of points.

It is observed from Table I, Table II, Table III and Table IV that there is a very good agreement between ADS simulation (exact values) and models results.

Fig. 2 shows the plots of noise parameters (minimum noise figure $F_{\min}$, normalized equivalent resistance R_n, magnitude of optimum reflection coefficient $\left|\Gamma_{opt}\right|$ and angle of optimum reflection coefficient $\angle\Gamma_{opt}$) versus frequency and bias conditions, obtained by the ANFIS model.

TABLE I: Specification of the Proposed ANFIS Model for F_{MIN}

Type	sugeno
Inputs/Outputs	11/1
No. of input membership function	1-2-3-2-1-1-1-1-2-2-1
No. of output membership function	48
Input membership function Types	Gaussian
Output membership function Types	Linear
Rules Weight	1
No. of fuzzy rules	48

TABLE II: SPECIFICATION OF THE PROPOSED ANFIS MODEL FOR R_N

Type	sugeno
Inputs/Outputs	11/1
No. of input membership function	1-2-2-2-1-1-1-1-2-3-1
No. of output membership function	48
Input membership function Types	Gaussian
Output membership function Types	Linear
Rules Weight	1
No. of fuzzy rules	48

TABLE III: SPECIFICATION OF THE PROPOSED ANFIS MODEL FOR $\left|\Gamma_{opt}\right|$

Type	sugeno
Inputs/Outputs	11/1
No. of input membership function	1-2-2-2-1-1-1-2-3-1-1
No. of output membership function	48
Input membership function Types	Gaussian
Output membership function Types	Linear
Rules Weight	1
No. of fuzzy rules	48

TABLE IV: SPECIFICATION OF THE PROPOSED ANFIS MODEL FOR $\angle\Gamma_{opt}$

Type	Sugeno
Inputs/Outputs	11/1
No. of input membership function	1-1-2-2-3-1-1-1-2-3-1
No. of output membership function	72
Input membership function Types	Π-shaped
Output membership function Types	Linear
Rules Weight	1
Number of fuzzy rules	72

TABLE V: THE MAXIMUM, MINIMUM AND MEAN RELATIVE ERROR PERCENTAGE FOR TESTING DATA OF ANFIS NETWORK

Noise parameter	Min	Max	Mean
$F_{\min}$	0.084	1.85	0.86
R_n	0.072	1.74	0.74
$Mag\left(\Gamma_{opt}\right)$	0.081	1.3	0.61
$Ang\left(\Gamma_{opt}\right)$	0.11	2.8	1.01

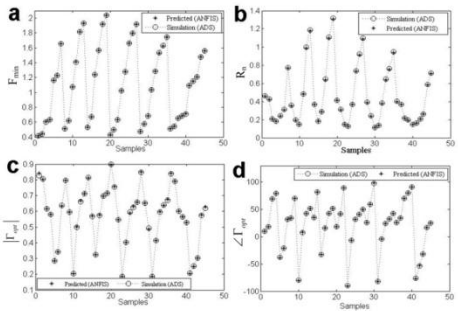

Fig. 2. The comparison between the simulation values and the predicted values using ANFIS model for testing data of : (a) Minimum noise figure, (b) Normalized equivalent resistance, (c) Magnitude of optimum reflection coefficient, (d) Angle of optimum reflection coefficient.

IV. CONCLUSION

In this paper, HEMT transistor noise parameters such as minimum noise figure $F_{\min}$, normalized equivalent resistance R_n , magnitude of optimum reflection coefficient $\left|\Gamma_{opt}\right|$ and angle of optimum reflection coefficient $\angle\Gamma_{opt}$ dependence on bias conditions, frequency and S-parameters, predicted with ANFIS model. The comparison between ADS simulation and predicted values using models shows that there is an excellent agreement between the predicted output characteristics of the device based on our models and a ADS simulation with least error. These networks can be designed in a short time with least error. Therefore, the proposed models can be used as efficient tools for noise modeling of HEMT transistor.

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