# HEMT Transistor Noise Modeling using Generalized Radial Basis Function

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*Abstract:* **In this paper, one important architecture of neural networks named a generalized radial basis function (GRBF) is applied in order to model HEMT Transistor Noise Parameters dependence on bias conditions such as dc drain-to-source voltage, dc drain-to-source current, frequency and S-parameters that can accurately predict transistor noise parameters in a wide frequency ranges for all bias points from the operating range including transistor S-parameters.**

*Keywords:* Generalized Radial Basis Function, HEMT Transistor, S-Parameters.

## I. INTRODUCTION

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. 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, 2].

In many of these cases, 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 [3- 5].

In this paper, a Generalized Radial Basis Function (GRBF) network 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 network. A simplified overview of proposed ANN model is shown in Fig. 1.

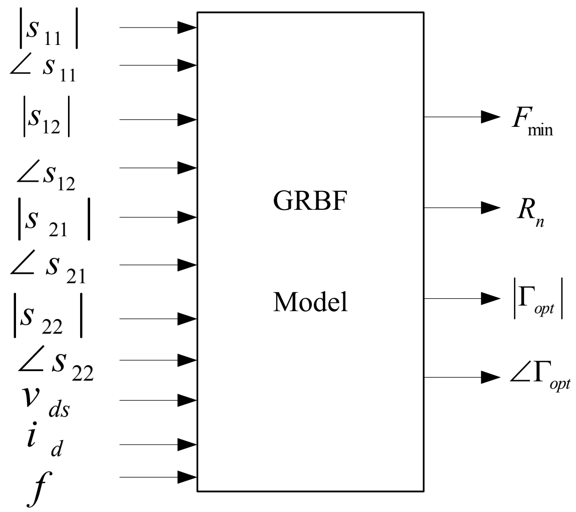


Fig. 1 A simplified overview of ANN model.

The GRBF network is a generalization of the RBF network, which allows to different variances for each dimension of the input spaces by replacing the radial Gaussian kernels with elliptical basis functions. The number of nodes in the hidden layer of the generalized RBF network is M, where M is ordinarily smaller than the number of neurons in the hidden layer of RBF network. In GRBF network, the linear weights associated with the output layer, and the positions of the centers of the radial basis functions and the norm weighting matrix associated with the hidden layer, are all unknown parameters that have to be learned[6].

## II. TRANSISTOR NOISE PARAMETERS

A two-port noisy component can be characterized by a noise figure F [1, 7], expressed as

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

where $F_{\min}$ is a minimum noise figure, $R_n$ is an equivalent noise resistance, $\Gamma_{opt}$ 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 $F_{\min}$, $\Gamma_{opt}$ and $R_n$ describe inherent behavior of the component and are independent of a connected circuit.

## III. GRBF NETWORK

Multilayer perceptron (MLP) neural networks have been applied in modeling of microwave transistor noise, dependence on frequency and bias conditions [8, 9]. In this paper, first we describe radial basis function (RBF) and then concentrate on the application of GRBF networks. A radial basis function network is a neural network approached by viewing the design as a curve-fitting (approximation) problem in a high dimensional space. Learning is equivalent to finding a multidimensional function that provides a best fit to the training data, with the criterion for best fit being measured in some statistical sense.

There are different learning strategies in the design of an RBF network depending on how the centers of RBF of the network are determined. There are three major approaches to determine the centers [6]:

i- Fixed Centers Selected at Random**:** In this approach, the locations of the centers may be chosen randomly from the training data.

ii- Self organized Selection of Centers: In the second approach, the radial basis functions can move the locations of their centers in a self-organized fashion.

iii- Supervised Selection of Centers: In the third approach, a supervised learning process is employed to obtain the centers of the radial basis function and all other free parameters of the network. In other words, the RBF network takes on its most generalized form.

A natural candidate for such a process is error correction learning, which is most conveniently implemented using a gradient-descent procedure that represents a generalization of the LMS algorithm.

Specifically, we consider an extension of the RBF network which allows a different variance for each input dimension. The relaxation of the radial constraint transforms the standard Gaussian kernels with circular symmetry into elliptic basis kernels, which can reduce the dimensionality of the input space. This scheme is denoted as GRBF network.

The learning algorithm chooses the GRBF centers one by one in order to minimize the output error. After selecting each new center from the training set, the centers and variances of the global network are optimized by applying gradient descent techniques.

The error function is given by

$$E = \sum_p \sum_k \left( y_k(v_p) - g_k(v_p) \right)^2$$

and the gradient equations for the variances and centers are

$$\frac{\partial E}{\partial \sigma_{ij}} = -2\sum_p \sum_k e_k(v_p) o_i(v_p) \lambda_{ik} \cdot \frac{1}{\sigma_{ij}} \left( \frac{v_{pj} - \mu_{ij}}{\sigma_{ij}} \right)^2$$

$$\frac{\partial E}{\partial \mu_{ij}} = -2\sum_p \sum_k e_k(v_p) o_i(v_p) \lambda_{ik} \cdot \frac{1}{\sigma_{ij}} \left( \frac{v_{pj} - \mu_{ij}}{\sigma_{ij}} \right)$$

where p indexes the input patterns, k the output dimensions, $v_p$ is the p$^{th}$ input pattern , $y_k(v_p)$ is the desired (measured) output, $g_k(v_p)$ is the output of the network, $e_k(v_p) = y_k(v_p) - g_k(v_p)$ is the network error and $o_i(v_p)$ is the output of neuron i with

$$o_i(v_p) = \prod_j \exp - \frac{(v_{pj} - \mu_{ij})^2}{2\sigma_{ij}^2}$$

$$g_k(v_p) = \sum_i \lambda_{ik} \prod_j \exp - \frac{(v_j - \mu_{ij})^2}{2\sigma_{ij}^2}$$

where i indexes the GRBF units, j the input dimensions and k the output dimensions.

## IV. 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. The training set was obtained by selecting 216 samples. we used our database for training the ANN model with MATLAB 7.0.4 program. In order to check the generalization capability, a test set containing 45 remained samples was used.

Test and training samples must be different and are selected randomly from the original database (ADS). In order to compare the accuracy of the model, the maximum, minimum and mean relative error for proposed ANN model was calculated. Table 1 shows the results for testing data, where the relative error for variable X is evaluated as

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

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

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

where $N_P$ is the number of points.

Table. 1 The maximum, minimum and mean relative error for testing data

| Noise parameter | Min | Max | MRE |
|---|---|---|---|
| $F_{\min}$ | 0 | 0.6 | 0.087 |
| $R_n$ | 0.0001 | 1.1 | 0.3 |
| $Mag(\Gamma_{opt})$ | 0.0001 | 1.6 | 0.33 |
| $Ang(\Gamma_{opt})$ | 0.87 | 5.87 | 0.31 |

The comparison of average error (AE %) between the train and test data is shown in Table 2, where the average error for variable X is evaluated as

$$\mathrm{AE\ \%} = 100 \times \frac{1}{\mathrm{N_P}} \sum_{i=1}^{\mathrm{N_P}} \left| \mathrm{X_{(sim)}} - \mathrm{X_{(pred)}} \right|_i$$

It could be seen that the value of AE% is less than 0.44 %.

Table. 2 The average error for training and testing data

| Noise parameter | Training | Testing |
|---|---|---|
| $F_{\min}$ | 0.05865 | 0.19186 |
| $R_n$ | 0.10001 | 0.37765 |
| $Mag(\Gamma_{opt})$ | 0.074342 | 0.18842 |
| $Ang(\Gamma_{opt})$ | 0.11771 | 0.43132 |

It is observed from Table 1 and Table 2 that there is a very good agreement between ADS simulation (exact values) and predicted data.

Fig. 2 shows the plots of noise parameters(minimum noise figure $F_{\min}$, normalized equivalent resistance $R_n$, magnitude of optimum reflection coefficient $|\Gamma_{opt}|$ and angle of optimum reflection coefficient $\angle\Gamma_{opt}$ ) versus frequency and bias conditions, obtained by the chosen model, at two different state: (1)training of samples (2)samples that does not belong to the training set i.e., test set.

The comparison between ADS simulation and predicted values of ANN model shows that there is an excellent agreement between the predicted outputs characteristics of the device based on our model and ADS simulation with least error.

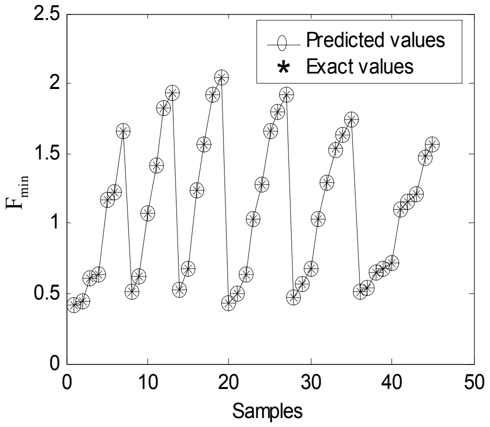


Fig. 2a Minimum noise figure $F_{min}$

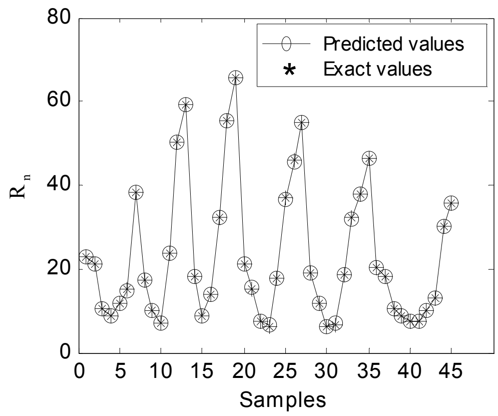


Fig. 2b Normalized equivalent resistance $R_n$

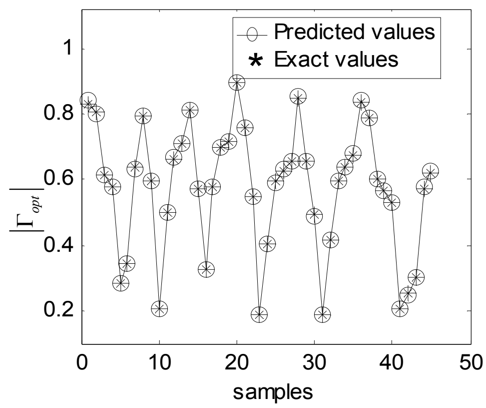


Fig. 2c Magnitude of optimum reflection coefficient $|\Gamma_{opt}|$

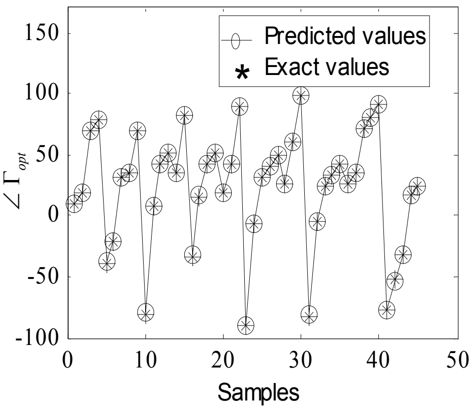


Fig. 2d Angle of optimum reflection coefficient $\angle\Gamma_{opt}$

## V. Conclusions

In this paper, one important architecture of neural networks named a generalized radial basis function is applied to model HEMT transistor noise parameters such as minimum noise figure $F_{\min}$, normalized equivalent resistance $R_n$, magnitude of optimum reflection coefficient $|\Gamma_{opt}|$ and angle of optimum reflection coefficient $\angle\Gamma_{opt}$ dependence on bias conditions, frequency and S-parameters.

An alternative learning procedure has been developed for the GRBF network. The GRBF network reduces drastically the number of units required to obtain an accurate model. This network can be designed in a short time. The comparison between ADS simulation and predicted values of proposed model shows that there is an excellent agreement between the predicted output characteristics of the device based on GRBF model and ADS simulation with least error, therefore, the proposed GRBF model can be used as an efficient tool for noise modeling of HEMT transistor.

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