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Design of Low Noise Amplifier of IRNSS using ANN

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ABSTRACT

Paper presents a Neural Network Modeling approach to microwave LNA design. To acknowledge the specifications of the amplifier, Mobile Satellite Systems are analyzed. Scattering parameters of the LNA in the frequency range 0.5 to 18 GHz are calculated using a Multilayer Perceptron Artificial Neural Network model and corresponding Smith charts and Polar charts are plotted as output to the model. This paper describes the design and measurement of a medium power amplifier (MPA) using 0.15µm GaAs PHEMT technology for wireless application. At 2.4 GHz and 3.0 V of VDS, a fabricated MPA exhibits a P1dB of 15.20 dBm, PAE of 12.70% and gain of 9.70 dB. The maximum current, Imax is 84.40mA and the power consumption for this device is 253.20mW. The die size of this amplifier is 1.2mm x 0.7mm.

I. INTRODUCTION

In this research, attention is paid to the modeling of the scattering (S–) parameters of a gallium nitride high electron mobility transistor (GaN HEMT) power amplifier for Cband satellites [1]. The S-parameters of a microwave transistor depend on the operating bias condition as well as on the frequency. Modeling of the S-parameters is based on application of artificial neural networks (ANNs). In the last two decades artificial neural networks have found their place as an efficient tool for modeling of microwave devices [2, 3]. ANN models are usually extracted from the measured data directly, without need for detailed knowledge about device physics, allowing them to encounter all effects contributing to the device behavior. ANN model is developed to obtain the microwave characteristics of the device which is further used to develop the ANN model for S-parameter extraction of pseudo orphic HEMT (High Electron Mobility Transistor). The calculated S-parameters, Gain and minimum Noise figure from the

ANN model are the parameters which are used to design the low noise pHEMT (Pseudo High Electron Mobility Transistor) power amplifier.

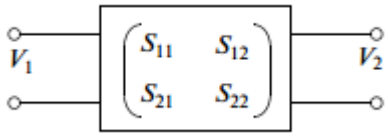

Figure 1: Generalized 2-port network

MICROWAVE TRANSISTOR SPARAMETER

Microwave transistors operating under small signal conditions can be characterized by the scattering parameters (S-parameters) which relate the voltage wave's incident on the ports to those reflected from the ports (Fig. 1). The scattering matrix, or S matrix, is defined in relation to these incident and reflected voltage waves as:

$$\begin{bmatrix} V_1 - \\ V_2 - \end{bmatrix} - \begin{bmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{bmatrix} \begin{bmatrix} V_1 + \\ V_2 + \end{bmatrix}$$

$$S_{ij} = \frac{V_i -}{V_j +} | V_k + = 0, \text{ Za } k \neq j$$

S_{ii} is the reflection coefficient seen looking into the port i when all other ports are terminated in load matches. S_{ij} is the transmission coefficient from port j to port i when all ports are terminated in matched loads. The S-parameters of microwave transistors are frequency, temperature and bias dependent [4].

II. Artificial Neural Networks method for Designing Low Noise Amplifier (LNA)

Neural networks are the processing systems having information with their design inspired by the ability of the human brain. These networks learn from interpretations and generalize by abstraction. A usual neural network arrangement consists of two kinds of simple components. One is processing elements and the other is interconnections between them. The processing elements are called as neurons and the connection among these processing elements are known as links or synapses [1]. For the last two decades ANNs are utilized repeatedly in speech, pattern recognition, signal processing and remote sensing etc. [6]. Figure 1 shows the architecture of multilayer perceptron (MLP). MLP is a popularly used neural network structure in modeling of devices. In the MLP neural network, these neurons are collected into layers [8]. This architecture associates several inputs and predicts outputs. As there are numerous layers in this architecture so this architecture is called multilayer perceptron. The hidden layer has so many hidden neurons. For the training of ANN, the number of hidden nodes in an ANN should be optimized so that network is trained perfectly. ANN models are usually extracted from the measured data directly. Without need for detailed knowledge about device physics, these models permit them to encounter all effects contributing to the device

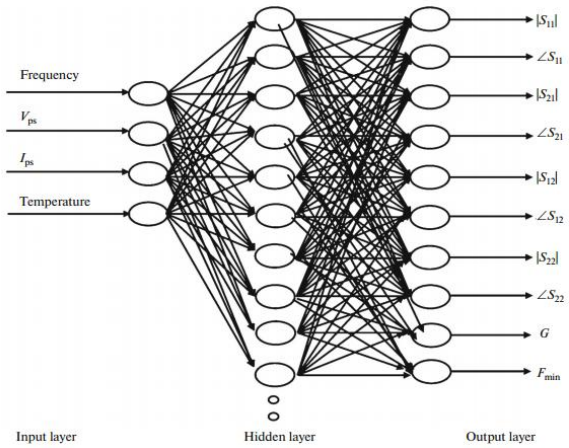

Figure 2: Neural network architecture

behaviour. ANN model is developed to acquire the microwave features of the device which is further utilized to cultivate the ANN model for scattering parameter extraction of pseudomorphic HEMT (High Electron Mobility Transistor).Minimization of NF and maximization of maximum available gain (MAG) generally possess opposite necessities. Minimum NF is obtained when the input impedance of LNA is made equivalent to the

characteristics impedance calculated at operating frequency. On contrary to this, MAG is obtained when input and output terminations are perfectly matched in characteristic impedance Zo. Generally these two complex impedances are never equal so an optimization scheme needs to be addressed. This model is utilized to extract parameters from the available measured data. For the designing of LNA, artificial neural network is trained using three layer architecture as described above. For training and implementing in the ANN toolbox (using neural fitting and network tool) of MATLAB software, Levenberg-Marqaurdt back propagation algorithm has been used. Experimental data for training of neural network are taken from the Agilent MGA72543 GaAs pHEMT Low Noise Amplifier datasheet. To verify the validity of the trained ANN model, experimental data [10] are compared with the results of present model.

III. MODELING METHODOLOGY

This paper proposes a solution to the problem thatstill makes use of the common MLP and RBF models, but within a modified ANN architecture. The idea is to find the design parameters in sequence, each one constraining the determination of the next one(s). First, an ANN is trained to correctly specify a first design parameter. It takes the set of desired performances as input and has only the chosen design parameter as output.

A. Neural Architecture

Two common ANN architectures are considered, the multilayer perceptron (MLP) [5] and the radial basis functions (RBF) model [6]. Both consist of three layers of neurons in sequence: an input layer, a hidden layer and an output layer.

1) MLP neural network: In the input layer, each neuron simply holds the value it receives. In the hidden layer, the output of a neuron j is given by

$$z_j = f\left(\sum_{i=1}^{M} \omega_i x_i\right) \quad (1)$$

where M is the number of afferent neurons, xi is the output of the ith input layer neuron, ωi is a weight to be determined and f() is an nonlinear output function, often the logistic sigmoid $f_{logsig}= 1/1+e^{n}$ or the hyperbolic tangent sigmoid $f_{tansig}= 2/1+e^{-2n}$ -1 . Within a given MLP, all the hidden layer neurons use the same transfer function. In the output layer, the neural outputs take also the form defined in equ. (1), but the identity function is usually chosen for the output function (linear output). As a result, the output of a neuron k is given by

$$y_k = \sum_{j=1}^{N} \omega_j z_j \quad (2)$$

Where N is the number of neurons in the hidden layer, z_j is the output of the j^{th} hidden layer neuron and ω_j is also a weight to be determined.

The neurons are grouped into layers in the MLP neural network. The first and last layers are called input and output layers, respectively. Between the input and the output layers, there exists a central part of the neural network called a hidden layer. Depending on the complexity of the input response and the desired output, the number of the hidden layers and the neurons at each layer can vary, because there always exists a three-layer

perceptron that can approximate an arbitrary nonlinear, continuous, multi-dimensional function f with any desired accuracy. Therefore, a typical MLP neural network consists of an input layer, a hidden layer and an output layer, as shown in figure 3.

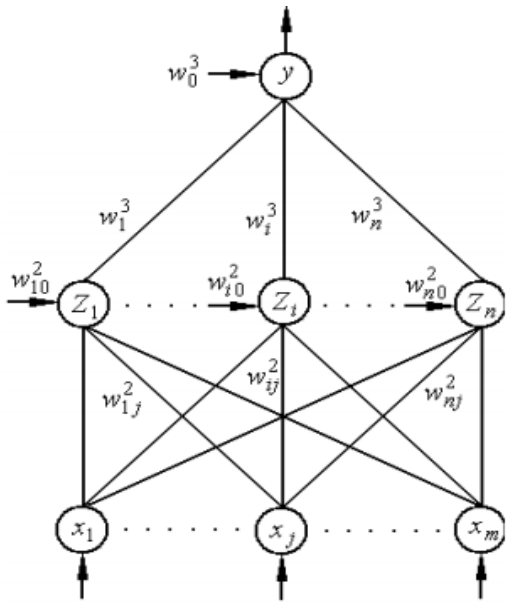

Figure 2: A three-layer MLP structure

For a given input x, the output of a three-layer MLP neural network can be computed by

$$y = w_0^3 + \sum_{i=1}^{n} w_i^3 \sigma \left(w_{i0}^2 + \sum_{j=1}^{m} w_{ij}^2 x_j \right) \quad (3)$$

i.e.

$$y = [w_0^3, w_1^3, \ldots, w_i^3, \ldots, w_n^3][1, Z_1, \ldots, Z_i, \ldots, Z_n]^T \quad (4)$$

The neural model is then trained to learn the input–output relationship from the training data (sample of input–output data). Specifically training is to determine the neural model parameters, i.e. neural network weights w^i_{ij}, such that the ANN model-predicted output best matches that of the training data. The testing data (new input–output samples) are used to test the accuracy of the ANN model.

B. Generic notation

Let n and m represent the number of input and output neurons of a neural network. Let x be an n-vector containing the external inputs to the neural network, y be an m-vector containing the outputs from the output neurons, and w be a vector containing all the weight parameters representing various interconnections in the neural network. The definition of w, and the manner in which y is computed from x and w, determine the structure of the neural network.

C. Neural network modeling approach

The neural network can represent the behavior of any microwave device only after learning the original x – y relationship through a process called training. Samples of (x- y) data, called the training data, should first be

generated from original device EM simulators or from the device measurements. Training is done to determine neural network weights w such that the neural model output best matches the training data. A trained neural network model can then be used during microwave design providing answers to the task it has learned. The original EM based microwave device modeling problem can be expressed as y=f(x) where f is the detailed EM based input–output relationship [2]. The neural network model for same device is defined as y= f (x, w). The neural-network approach can be compared with conventional approaches for a better understanding. The first type is the detailed modeling approach such as EMbased models for passive components and physics-based models for active components. The overall model, ideally, is defined by a well-established theory and no experimental data is needed for model determination. However, such detailed models are usually computationally expensive. The second type is an approximate modeling approach, which uses either empirical or equivalent-circuit-based models for passive and active components. The evaluation of approximate models is much faster than that of the detailed models. However, the models are limited in terms of accuracy and input parameter range over which they can be accurate. The neural-network approach is a new type of modeling approach where the model can be developed by learning from accurate data of the RF/microwave component. After training, the neural network becomes a fast and accurate model representing the original component behaviors.

D Network size and layers

For the neural network to be an accurate model of the problem to be learned, a suitable number of hidden neurons are needed. The number of hidden neurons depends upon the degree of non-linearity of f and the dimensionality of x and y (i.e., values of n and m). Highly nonlinear components need more neurons and smoother items need fewer neurons [3]-[4]. However, the universal approximation theorem does not specify as to what should be the size of the MLP network. The precise number of hidden neurons required for a given modeling task remains an open question. So, either by experience or a trial-and-error process is used to judge the number of hidden neurons. The appropriate number of neurons can also be determined through adaptive processes, which add/delete neurons during training. The number of layers in the MLP can reflect the degree of hierarchical information in the original modeling problem. In general, the MLPs with one or two hidden layers (i.e., three- or four-layer MLPs) are commonly used for RF/microwave applications.

V. RESULTS AND DISCUSSION

Completion of training, the models developed get tested and evaluated. This included the evaluation of the network's ability to learn the mappings of the training data, as well as its ability to generalize on the test set data. Each test vector is used as input to the respective ANN.

The computed outputs represent the modeled -parameters at the input frequency for each test inductor

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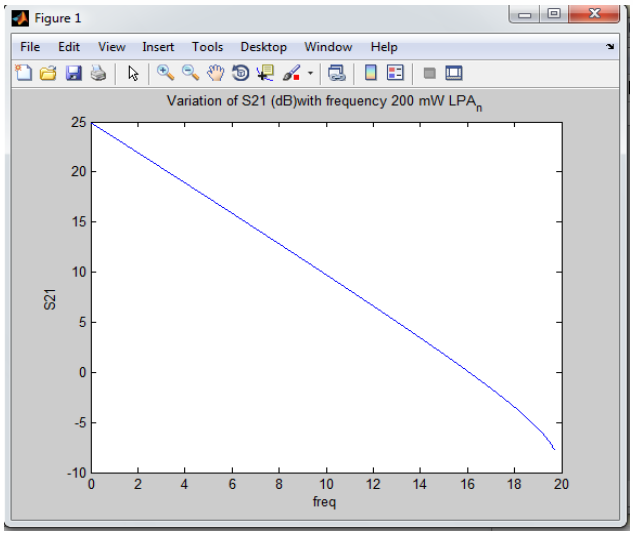

Figure 5.1: S21 variation bandwidth with different frequencies for LNA

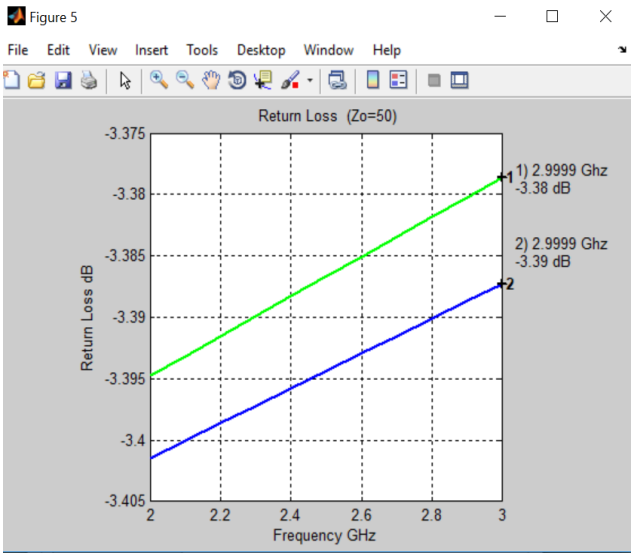

Figure 5.2: Return Loss variation bandwidth with 2.2 GHz frequencies for LNA

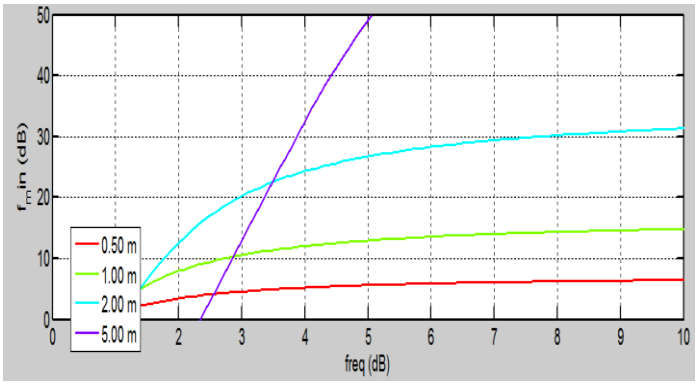

Figure 5.3: Fm(dB) variation bandwidth with different frequencies at 0.50 ,1.0,2.0,5.0 etc.

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Gain with frequency range 0.1–10 GHz at the same bias condition as the forward transmission coefficient. The gain decreases with an increase low level position in frequency and the down is steep in the frequency range of 0– 2.2 GHz

Below figure 5.4, 5.5, 5.6, 5.7 are as *S*11, *S*22–*S*11 and *S*22 are plotted on smith charts and polar chart inrespectively. *S*11 is equivalent to input complex reflection coefficient (*Γin*) and *S*22 is equivalent to output complex reflection coefficient (*Γout*). At the centre of the smith and admittance different angle rotator chart, reflection is zero (|*Γ* | = 0) and at the periphery of thesmith chart reflection is maximum optimized with neural network LM data sheet(|*Γ* | = 1).

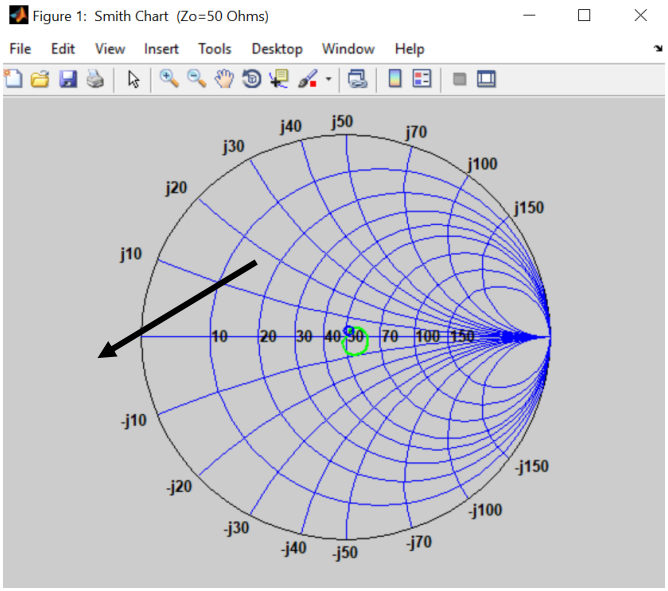

Figure 5.4: Fm(dB) variation bandwidth with different résistance *S*11: Input Reflection Coefficient (Smith Chart)

This indicates that the magnitude of *S*11 and *S*22 should always be less than 1, otherwise, all the incident waves will be reflected in different frequencies level.

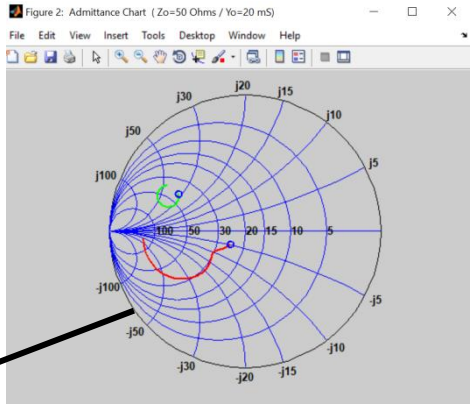

Figure 5.5: Fm(dB) variation bandwidth with different résistance *S*22: Output Reflection Coefficient (Smith Chart)

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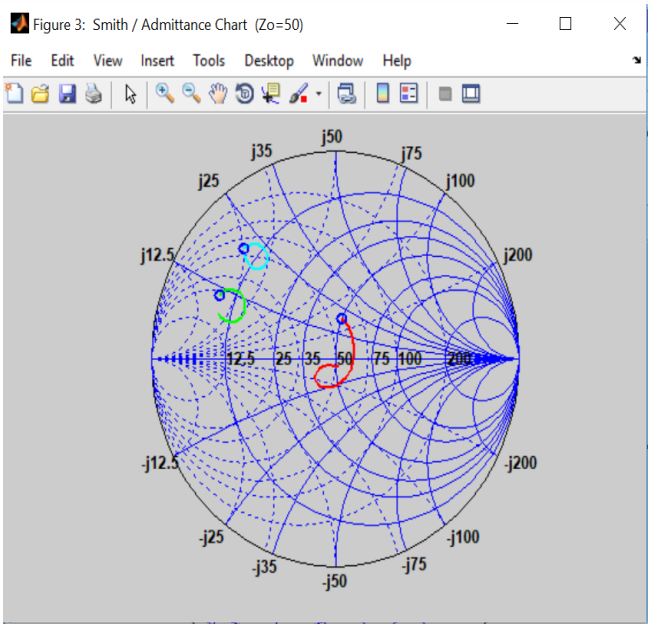

Figure 5.6: *S*12: Reverse Transmission Coefficient (Polar Chart)

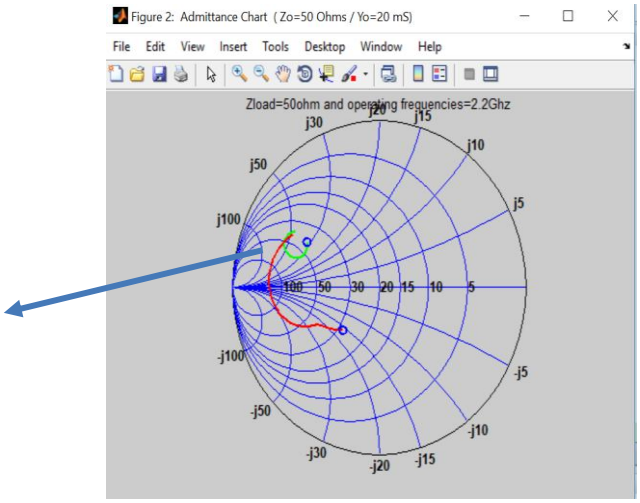

Figure 5.7: S21: Forward Transmission Coefficient (Polar Chart)

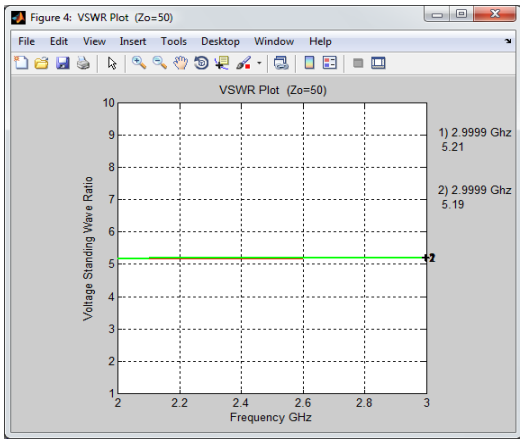

Figure 5.8: VSWR Plot at 2.2 operating frequencies

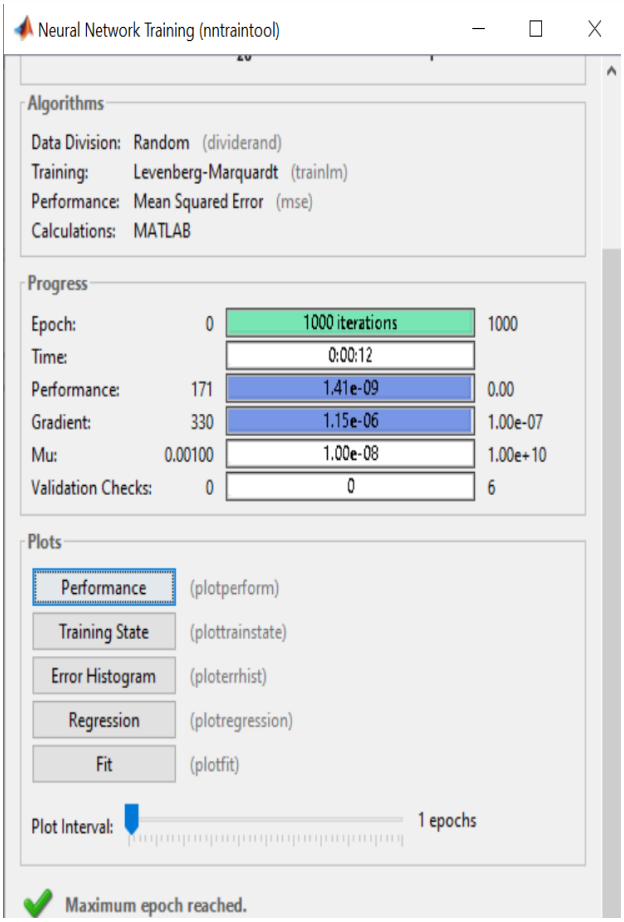

Figure 5.9: Train Data using Neural Network –LM with random diversion data sheet

Above neural network specifies that validation error for Root Mean square error plot is 0.00022 .at 1000 iteration in our proposed approach .

VI. ACKNOWLEDGMENT

I sincerely thanks Ajay Kumar Garg engineering college Ghaziabd for giving me the right guidance, opportunity and working environment for my research work

VII. CONCLUSION

An approach for the microwave nonlinear device modelling technique based on the combination of the conventional equivalent circuit model and the artificial neural network (ANN) is presented in this paper. The main advantage of the proposed method is that the integration and differential of the ANN can directly be carried out from the original ANN. The proposed technique is very useful for neuralbased microwave computer-aided-design, and for analytically unified dc, small signal and nonlinear device modeling

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