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An extraction technique for small signal intrinsic parameters of HEMTs based on artificial neural networks

M. Hayati [a,b,*], B. Akhlaghi [a]

[a] Electrical Engineering Department, Faculty of Engineering, Razi University, Tagh-E-Bostan, Kermanshah 67149, Iran
[b] Computational Intelligence Research Centre, Razi University, Tagh-E-Bostan, Kermanshah 67149, Iran

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ABSTRACT

This paper presents a fast and accurate procedure for extraction of small signal intrinsic parameters of AlGaAs/GaAs high electron mobility transistors (HEMTs) using artificial neural network (ANN) techniques. The extraction procedure has been done in a wide range of frequencies and biases at various temperatures. Intrinsic parameters of HEMT are acquired using its values of common-source S-parameters. Two different ANN structures have been constructed in this work to extract the parameters, multi layer perceptron (MLP) and radial basis function (RBF) neural networks. These two kinds of ANNs are compared to each other in terms of accuracy, speed and memory usage. To validate the capability of the proposed method in small signal modeling of GaAs HEMTs, data and modeled values of S-parameters of a 200 μm gate width 0.25 μm GaAs HEMT are compared to each other and very good agreement between them is achieved up to 30 GHz. The effect of bias, temperature and frequency conditions on the extracted parameters of HEMT has been investigated, and the obtained results match the theoretical expectations. The proposed model can be inserted to computer-aided design (CAD) tools in order to have an accurate and fast design, simulation and optimization of microwave circuits including GaAs HEMTs.

1. Introduction

Compared with bipolar transistor devices, field effect transistor (FET) devices have a better noise performance. Specially, GaAs metal extended semiconductor FETs (MESFETs) are widely used at microwave frequencies, due to their low noise and high gain characteristics. Their performance can be enhanced if a heterojunction is used between GaAs and AlGaAs, such as in high electron mobility transistors (HEMTs). GaAs HEMTs are rapidly replacing conventional MESFET technology in military and commercial applications. They are promising devices for millimeter-wave applications and optical communication systems due to their excellent high frequency and low noise performance [1–3]. Currently low noise HEMTs are used in front end of satellite communications, radio astronomy and satellite direct broadcasting receiver systems [3,4].

An accurate extraction method for a proper small signal equivalent circuit of HEMTs is necessary for designing a circuit and evaluating the process technology. It also allows the development of accurate and yield-effective computer-aided design (CAD) of monolithic microwave integrated circuits (MMICs) and optoelectronic integrated circuits (OEICs) [5,6].

Several approaches are used to model small signal active devices. Some of these techniques include table-based models, temperature-dependent nonlinear models, and artificial neural networks (ANNs). These models are then utilized for computer-aided design and optimization of microwave circuits [7].

ANN computational models have gained recognition as an unconventional and useful tool for microwave modeling and design (including component or circuit level) [8,9]. Fast, accurate and reliable neural network models can be developed from measured or simulated microwave data through a process called training. Neural network transistor models for a new semiconductor device can be developed even if the device theory/equations are unavailable [8]. That is to say, ANN technique is useful in modeling microwave devices because it can generalize, that means the model can respond to new data that have not been used during training process. ANN techniques are time saving comparing to temperature-dependent and table-based nonlinear models since require only a few algebraic operations.

In some previous literatures, ANN techniques have been applied to extract equivalent circuit parameters (ECPs) of some microwave components and circuits including heterojunction bipolar transistors (HBTs) [10] and MESFETs [7,11]. Some large signal modeling of HEMTs has been reported in previous literatures [12–14]. Some

* Corresponding author at: Electrical Engineering Department, Faculty of Engineering, Razi University, Tagh-E-Bostan, Kermanshah 67149, Iran.
E-mail address: mohsen_hayati@yahoo.com (M. Hayati).

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literatures [15,16] have presented a small signal model for HEMT using ANN. Advantages of the present work in contrast with previous literatures are that in the proposed method, two kinds of neural networks, i.e. multi layer perceptron (MLP) and radial basis function (RBF) networks, are constructed for extraction of intrinsic parameters of HEMT. Then these networks are compared to each other in order to determine the best neural model in terms of accuracy, speed and memory usage. Moreover, because parameters of temperature and frequency could alter the overall performance of the circuit, the device model must take into account these parameters [7,17,18]. Therefore, in this work temperature and frequency in addition to bias points are considered as inputs of the proposed neural models while in previous publications only bias points are applied to the input of the network.

The rest of the paper is organized as follows: Section 2 deals with the modeling methodology, which consists of two subsections: in Section 2.1 intrinsic and extrinsic elements of small signal equivalent circuit of GaAs HEMT at microwave frequencies are introduced. In Section 2.2 neural network modeling methodology is given as follows: Sections 2.2.1 and 2.2.2 describe the MLP and RBF network structures respectively, and the learning algorithm for each networks' parameters. In Section 3, we present structures of the implemented neural networks. Error analysis and comparison of two neural networks are presented in Section 4. Section 5 presents small signal modeling validation of the proposed ANN models. Finally, in Section 6 the main conclusions are summarized.

2. Modeling methodology

2.1. Extraction of intrinsic elements from measured S-parameter values

Fig. 1 shows small signal equivalent circuit of AlGaAs/GaAs HEMT in its common-source format. It can be partitioned into two basic parts: extrinsic elements consist of parasitic capacitances, inductances and resistances. These elements account for non-desired effects or represent the connections of the intrinsic part to another device in a complete circuit and are bias-independent, and intrinsic elements, which consist of R_{gs} (channel resistance), g_{ds} (drain conductance), g_m (transconductance), τ (time delay associated with transconductance), C_{gs}, C_{gd}, C_{ds} (gate to source, gate to drain and drain to source capacitances, respectively) and are bias-dependent.

The basic cell for linear, nonlinear and noise model is intrinsic transistor [3], so this work focuses in taking out the intrinsic elements. The small signal ECP extraction methodologies can be classified into two categories: optimization-based and direct extraction (analytical) techniques [5,19,20]. The optimization procedures [21–23] may cause element values with no physical sense, and the results depend on the initial guess values or the optimization method itself. The analytical procedures [1,3,5,20,24–29] overcome these drawbacks and allow extracting ECPs straightforwardly.

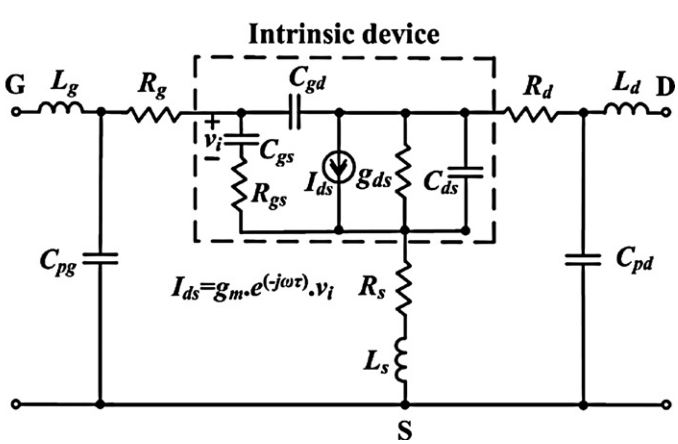

Fig. 1. Small signal equivalent circuit of GaAs HEMT.

In direct extraction method, the intrinsic elements are extracted according to the following steps [5]:

Step 1. The extrinsic elements are extracted from two sets of S-parameter measurements under 'cold' bias condition (V_{ds} = 0 V, i.e. passive device), which include of 'unbiased cold' (V_{ds} = 0 V and V_{gs} = 0 V) and 'pinched cold' (V_{ds} = 0 V and $V_{gs} < V_p$), where V_{gs} is gate-source voltage, V_{ds} is drain-source voltage, and V_p is pinch off voltage.
Step 2. S-parameter measurements are done under 'hot' bias condition (V_{gs} < 0 V and V_{ds} > 0 V, i.e. active device).
Step 3. Contribution of the extrinsic elements is removed from this set of S-parameters (i.e. obtained from 2nd step).
Step 4. The intrinsic parameters are analytically obtained from this new set of S-parameters (i.e. obtained from 3rd step).

The direct extraction technique for obtaining extrinsic and intrinsic elements of HEMT is described in details in [26]. The aim of this paper is to use the data obtained from the stages 1–4 to create an accurate ANN model for parameter extraction of HEMT.

2.2. Neural network model

For extraction of small signal intrinsic parameters of HEMT addressed in this paper, we consider implementation with two neural network structures. The first of these was a feed forward MLP neural network with training according to scaled conjugate gradient algorithm (trainscg) optimization. The second was a RBF network. The MLP and RBF networks have four inputs, i.e. V_{gs}, V_{ds}, *freq* (frequency) and T (operating temperature) and eight outputs, i.e. C_{ds}, C_{gd}, C_{gs}, R_{gs}, g_{ds}, g_m, τ and f_T (cut off frequency).

We start with a review of basic concepts of the MLP approach, and then we will describe the RBF network. All simulations and tests for the MLP and RBF networks are done using MATLAB's neural network toolbox.

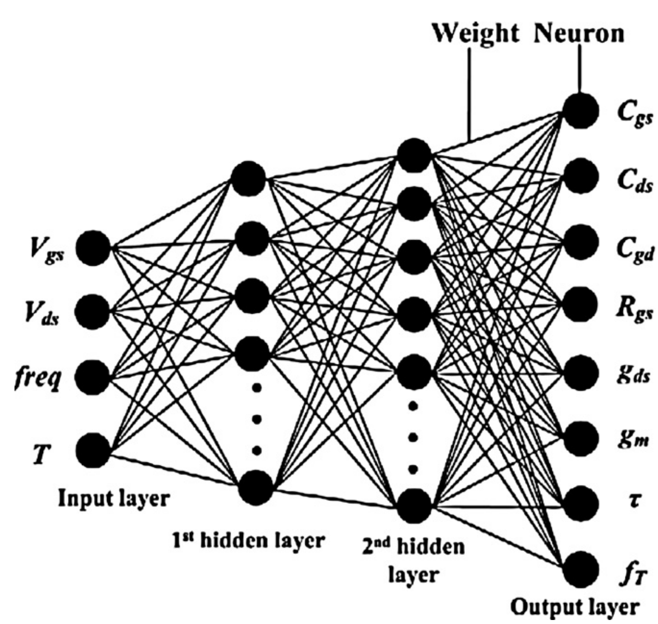

Fig. 2. Schematic of the proposed MLP neural network model.