Hybrid PKI Temperature Dependent Small-Signal Model of Microwave Transistors

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Abstract – **In this paper we are proposing a temperature-dependent small-signal model of microwave transistors. It consists of an empirical small signal model based on a device equivalent circuit and a prior knowledge artificial neural network. This model is more efficient and more accurate then an earlier proposed hybrid empirical-neural that include dependence on the ambient temperature. The proposed models has been developed for a pHEMT device and the obtained modeling results are contrasted to the reference values and to the values obtained by the earlier proposed hybrid model. Comparison of the modeling results prove advantages of the model proposed in the paper over the earlier proposed hybrid model.**

Keywords – **artificial neural network, microwave transistors, small-signal model, temperature dependence**

I. Introduction

Small-signal and noise modeling of low noise microwave transistors require special care in the computer-aided design of active circuits used in modern wireless systems. Extensive work has been carried out in the field of signal and noise modeling of these devices. Their physical models are too complex and require many input technological parameters, therefore the empirical models, mostly based on equivalent circuits are often used, [1]. Transistor small-signal characteristics are temperature dependent, but most of the existing transistor small-signal models are valid only for a specific ambient temperature. Therefore, for each given temperature point, it is necessary to extract the elements of the model. Extraction is basically an optimization process that can be time-consuming. Furthermore, the measured values of S-parameters for a given temperature point are requested for the extraction, which could take much efforts and time, since the temperature dependent measurements require special equipment and procedures.

In order to overcome the mentioned problems, in the earlier work, we have proposed the procedure for prediction of scattering (S-) parameters of microwave MESFETs and HEMTs for various device ambient temperatures, [2] and [3]. That model is a kind of hybrid empirical-neural models. An artificial neural network (ANN) is trained to predict temperature dependence of elements of the device equivalent circuit (ECP – Equivalent Circuit Parameters). Values of S-parameters are calculated within a microwave simulator for the ECP predicted by an ANN for a given temperature. ANNs have been chosen as a modeling tool since they have the ability to learn from the presented data, and therefore they are especially interesting for problems not fully mathematically described. It should be noted that they fit non-linear dependencies better than polynomials. There are many papers referring results of applications of the neural networks in the microwave area, [2]-[10].

The earlier proposed hybrid model has two potentional drawbacks: time-consuming extraction of ECPs required for collecting data for ANN training and modeling errors due to insufficiently accurate extraction of ECPs.

Here, we are proposing a new hybrid empirical-neural model based on empirical equivalent circuit and a prior knowledge input (PKI) ANN, in order to overcome the mentioned drawbacks. The model and its development are described in the paper. An example of modeling the specific device is provided as well. In order to prove advantages of the model the obtained results are contrasted to the reference (measured) values and values obtained by using the earlier proposed hybrid model.

II. Artificial Neural Networks

A standard multilayer perceptron (MLP) artificial neural network is shown in Fig. 1, [4]. This network consists of an input layer (layer 0), an output layer (layer N_L), as well as several hidden layers.

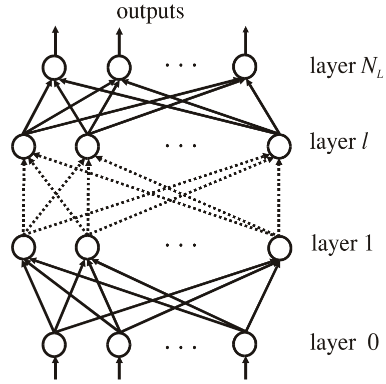

Fig. 1. MLP artificial neural network

Input data vectors are presented to the input layer and fed through the network that then yields the output vector. The l-th layer output is:

$$\mathbf{Y}_l = F(\mathbf{W}_l \mathbf{Y}_{l-1} + \mathbf{B}_l) \qquad (1)$$

where $\mathbf{Y}_l$ and $\mathbf{Y}_{l-1}$ are outputs of l-th and (l-1)-th layer, respectively, $\mathbf{W}_l$ is a weight matrix between (l-1)-th and l-th layer and $\mathbf{B}_l$ is a bias matrix between (l-1)-th and l-th layer.

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Function F is an activation function of each neuron and, in our case, is linear for input and output layer and sigmoid for hidden layers. The sigmoid function is:

$$F(u) = 1/(1+e^{-u}) \tag{2}$$

The neural network “learns” relationship among sets of input-output data (training sets) that are characteristics of the device under consideration during an optimization process, called the ANN training. The most common training algorithms are based on backpropagation algorithm, [6]. The backpropagation training algorithm can be described shortly as follows. First, input data vectors are presented to the input neurons and output vectors are computed. These output vectors are compared with desired values and errors are computed. Error derivatives are then calculated and summed up for each weight and bias until whole training set has been presented to the network. These error derivatives are used to update the weights and biases for neurons in the model. The training process proceeds until errors are lower than prescribed values or until maximum number of epochs (epoch is the whole training set processing) is reached. Once trained, the network provides fast response for all vectors from the input space without any additional change of its structure or its parameters. Furthermore, it provides correct response for the input values completely different from training ones, i.e. it is said that a trained ANN has a capability of generalization.

III. HYBRID EMPIRICAL-NEURAL SMALL SIGNAL MODEL OF FETS/HEMTS

In this paper we are considering a standard empirical model of microwave FET/HEMT transistors based on an equivalent circuit modification. A schematic of a packaged FET/HEMT equivalent circuit is shown in Fig.2.

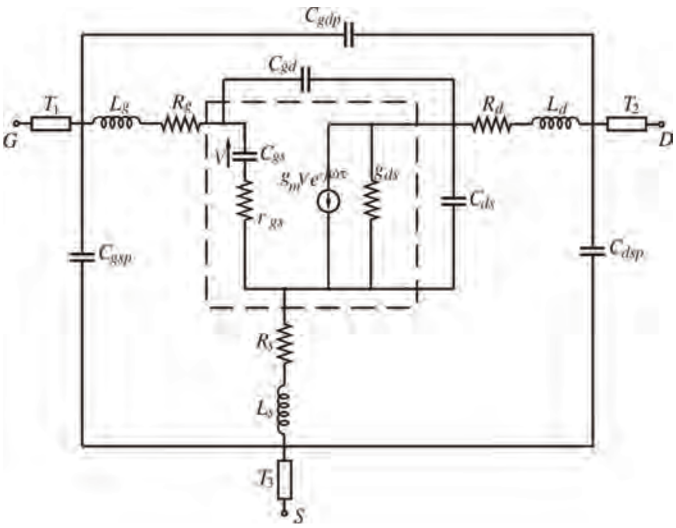

Fig.2. MESFET / HEMT package equivalent circuit

The intrinsic circuit (denoted by a dashed line) which is common for most of the transistor models is embedded in a network representing device parasitics.

The equivalent circuit parameters (ECP) are extracted from the measured values of the device scattering (S-) parameters. Since the model is valid only for one ambient temperature at which the S-parameters used in the extraction processes were measured. For any other temperature from the temperature range it is necessary to repeat measurements at that temperature and extract ECP values corresponding to that temperature. In order to avoid repeating of these procedures for any other temperature, and to include the dependence on temperature into the model, a hybrid empirical-neural model was proposed in [2]. The principle is shown in Fig.3.

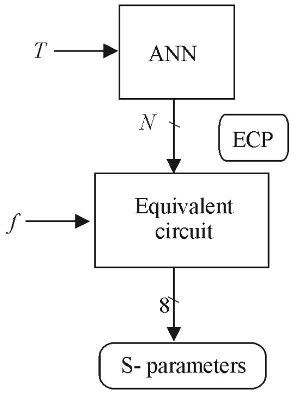

Fig.3. Hybrid empirical-neural model

For the purpose of the ECP determination versus temperature it has been proposed to add to the model an MLP neural network with one hidden layer. It has one neuron in the input layer corresponding to the ambient temperature (T), while the number of the neurons in the output layer corresponds to the number of temperature dependent ECP (let this number be denoted as N). The network is trained using extracted ECP values for certain number of operating temperatures. After the training is done, ECP for any temperature from the operating temperature range are determined by simple finding neural network response.

IV. HYBRID PKI EMPIRICAL-NEURAL MODEL

In order to increase modeling efficiency further, a new approach is proposed. Instead of temperature dependent ECP, in the proposed model ECP are assumed to be constant having the values that correspond to a single temperature (here we have chosen 20°C). The temperature dependence of S-parameters in introduced by an ANN trained to predict values of S-parameters for given temperature and frequency. The ANN is a PKI (*Prior Knowledge Input*) ANN that has additional knowledge at its inputs, [4]. In this case the prior knowledge is represented by the values of S-parameters obtained by the empirical model for T=20°C, Fig.4. Targets for the ANN training process are measured values of S-parameters for each temperature-frequency pair chosen for the training purposes.

Number of hidden layers (mostly one or two) and a number of neurons in the hidden layer(s) are not known a priori. Too many hidden neurons require more CPU time and can result in network over-learning and too few neurons may result in network under-learning. During the network training, neural networks with different number of hidden neurons are trained and validated. After the validation process, a network that gives the best prediction results is chosen as the noise model for the device.

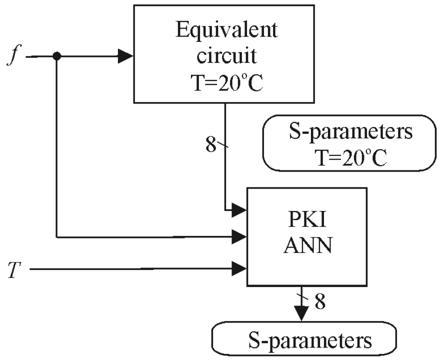

Fig.4 Hybrid PKI empirical-neural model

The proposed model is implemented in a microwave circuit simulator as follows: The first step is extraction of the ECP for the reference temperature (here 20°C) in the microwave simulator. It is done before the ANN training. The next step of implementation is done after the ANN was trained. It is performed within ANN training environment by generating mathematical expressions corresponding to the chosen ANN. Further, these expressions are put into VAR (Variable and Equation) block on the device schematic in the circuit simulator. Inputs of that VAR block are temperature frequency and values of S-parameters obtained by the empirical model for that frequency. Outputs of the VAR block are the final values of the S-parameters of the considered device. In that way prediction of S-parameters at any temperature and frequency from the device operating ranges is enabled, while the number of the necessary ECP extractions is reduced.

V. NUMERICAL RESULTS

The proposed method has been applied to a packaged microwave HEMT, type NE20283, from NEC. Measured values of S-parameters over the temperature range from –40°C to 60°C (20°C step) were used for the development of the model. These data had been obtained earlier at the University of Palermo, Italy [11].

First, the ECP of small-signal model were extracted from the available measured data for the temperature T=20°C. Then, the values of the S-parameters are simulated in the (6-18) GHz frequency range, with a 0.2GHz step and an appropriate training set was formed. After the ANN training process, a network with two hidden layers consisting of five and two neurons, respectively, was chosen and implemented into the microwave simulator ADS, [12].

As an illustration, in Fig.5 and Fig 6, temperature dependences of magnitudes of S_{11} and S_{21} parameters, respectively, are given. The measured (reference) values are represented by symbols and values obtained by the first hybrid model by dashed lines. Solid lines represent values obtained by the proposed model hybrid PKI model. One can observe that values obtained by both of the hybrid models are very close one to each other and the both are very close to the reference values.

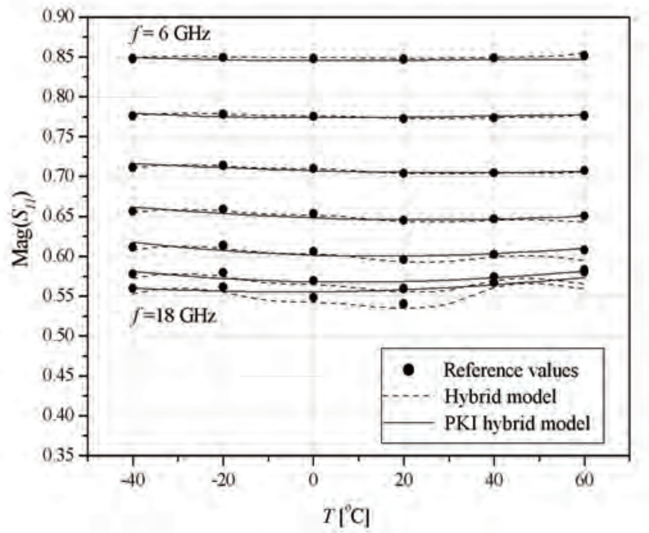

Fig.5 Magnitude of S_{11} parameter

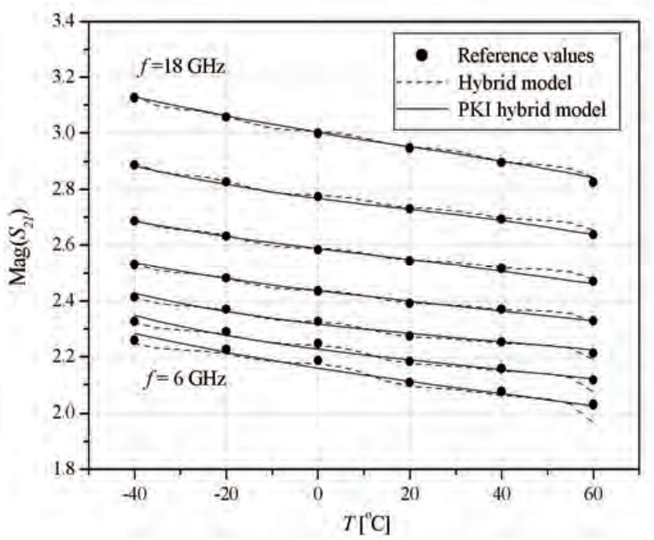

Fig.6 Magnitude of S_{21} parameter

VI. CONCLUSION

During the development of the proposed hybrid PKI empirical neural model extraction of ECP is done only once, therefore it is less time consuming than the previously proposed hybrid model.

Moreover, in the previously proposed hybrid model, the ANN is trained using the extracted values of ECP, and therefore if extraction was not done with a sufficient accuracy it will result in a degradation of the accuracy of the model. But, since the ANN in the proposed model is trained using measured values of S-parameters the model is less sensitive to the accuracy of ECP extraction than the hybrid model.

The both advantages over the hybrid model, increasing of the modeling efficiency and more accurate modeling, make the proposed model to be a convenient solution for the temperature dependent small-signal modeling of microwave FETs/HEMTs.

Implemented in a microwave simulator, the proposed model can be used a user-defined library element representing the considered device. It has the temperature as the input and can be used for prediction of the S-parameter in the whole temperature range without changes in its structure and avoiding need for additional measured data acquiring and optimisation procedures.

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