ARTIFICIAL NEURAL NETWORK APPROACH FOR MMIC PASSIVE AND ACTIVE DEVICE CHARACTERIZATION

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ABSTRACT

Artificial neural networks (ANNs) are presented for the fast and accurate modeling of passive and active devices in MMICs. ANNs trained with *S*-parameter over a wide range of frequencies were used for rectangular spiral inductor modeling and HEMT device small-signal models. After training and testing the ANN *S*-parameter model can be implemented as a two-port network into commercial circuit simulators. This enable the ANN model to be used in the design, analysis, and optimization of microwave circuits. A combination of ANN models trained with *S*-parameter and dc drain current measurements was implemented into an HP microwave circuit simulator to provide a small-signal bias-dependent active model. The proposed technique is capable of providing easy, fast and accurate simulation models for MMIC components where models based on equivalent circuit parameters (ECPs) do not exist or are not accurate over the desired region of operation.

INTRODUCTION

For MMIC design, the effectiveness of modern computer-aided design (CAD) methods relies on accurate models of active and passive circuit elements. Typical circuit simulator supplied passive and active element models do not accurately account for the parasitic and coupling effects which occur at microwave/millimeter-wave frequencies. On the other hand physical models, altough accurate, require skilled knowledge of physical devices and technology. Look-up table models are generally limited to a small number of input parameters and the data storage requirement can be large.

ANN-based models, trained with measurement data, can be easily yield with the same degree of accuracy. After training, model verification relies on test samples not present in the training dataset. In fact, the ANNs have an excellent interpolation capability to generalize the model over range of parameters not used for training. If inserted into a commercial microwave circuit simulator, the ANN models can be used for design, analysis, and optimization of microwave circuits. Simulation results approach the accuracy of the provided data used for characterization, without increasing the analysis time significantly since only a few algebraic operations are required. Once developed the library generation method can be used for different devices and material systems saving resources and time.

The neural network used in this application is a multilayer, feed-forward ANN, utilizing the *trainoss* learning algorithm, provided by the *Matlab*™ neural network tool. The network architecture consists of an input layer, an ouput layer, and one hidden layer of computing nodes termed neurons. Neurons of adjacent layers are connected each other through adaptive weights. The hydden layers, which incorporate nonlinear activation functions, allow modeling of complex input/output relationships between multiple input and multiple outputs. The hidden layer have a number of neurons which has to be optimized to obtain the best model accuracy. The nonlinear transfer function used for the neurons in the hidden layers is the tan-sigmoid function, which is expressed as $f(net) = \frac{2}{1+e^{(-2net)}} - 1$ where *net* is the weighted sum of the inputs. For the output layer either the tan-sigmoid or the linear transfer function were used. A schematic of a 2-input-2-outputs neural network with one hidden layer is shown in **Fig.1**.

PASSIVE DEVICE MODELING

As an application example the S-parameters of a rectangular square spiral inductors for different sizes and frequencies (2-12 GHz), resulting from a microwave CAD model, are modeled through an ANN approach [1], even if training data are often supplied by EM simulations in this case.

Inputs to the neural network are the physical dimensions of the inductor and the desired frequency. The outputs are the S-parameters at the respective frequency point, except for s_{12} which is equal to s_{21} for reciprocity. The input data are trace width (W) and spacing (S), hole size (H), and number of turns (T). The hole size (H) was swept instead of the side length (L) for the inductor to be physically realizable for each parameter combination. Further inputs obtained from combinations of input data and correlated in some way with the outputs helped to reduce network size, speed up the training and improve accuracy in the neurocomputing results [2]. Some combinations demonstrated to be more suitable to decrease error and computation time, such as the $L{\cdot}f$, $H{\cdot}f$ and $W{\cdot}S^{-1}$ products. The larger number of input terminations was compensated by a smaller optimised number of neurons in the hidden layer, which resulted to be as 10. The block diagram of the ANN model with the parameter sweep intervals is shown in **Fig.2a**.

Scattering plots of the ANN-computed values versus the CAD simulated values for test data are shown in **Fig.3** to visually illustrate the modeling accuracy. Perfect accuracy would result in the data points forming a straight line along the diagonal axis.

ACTIVE DEVICE MODELING

An ANN model for a δ-doped 0.2x100μm HEMT, mapping bias voltages V_{gs} and V_{ds} and frequency directly to S-parameters, over the whole operational range of frequencies (1-40 GHz) and bias voltages, including the pinchoff and the resistive regions, was generated [3]. The final model, shown in **Fig.2b**, required a two-stage network, where the outputs of the first stage, that is the s_{11}, s_{12} and s_{22} parameters, become correlated inputs to the second stage, modeling the more complex behaviour of the s_{21} parameter [4]. Despite of the use of two networks, the number of neurons has been drastically decreased, while achieving better accuracy in all bias regions. The training dataset consisted of 600 samples (measurements), each at 20 frequency points. A typical modeling result, comparing modeled and measured S-parameters for each bias point and frequency is shown in **Fig.4**. A second model was generated by determining the drain current I_{ds} from the bias voltages V_{gs} and V_{ds} (**Fig.5a**). A 3D plot comparing modeled and measured drain current point data is presented in **Fig.5b**. A very good fit with a very low percentage average error was reached in both cases.

The two ANN models were implemented as a unique device model onto a commercial microwave simulator (HP ADS) where both S-parameters and I_{ds} are expressed as a function of the bias voltages V_{gs} and V_{ds} . The resulting composite model for circuit simulation, schematized in **Fig.6**, can predict accurate small-signal device performance. It was applied to the design and optimization of microwave amplifiers, especially when a large number of active devices are to be used.

CONCLUSIONS

This neural network approach demonstrates that the small-signal performance of passive and active elements at microwave and/or millimeter-wave frequencies can be accurately predicted without the need to develop costly equivalent-circuit based model libraries. Once the network is trained, the computational time of the modeled outputs is negligible. The ANN S-parameter model, implemented as a two-port network into commercial circuit simulators, can be used in the design, analysis, and optimization of microwave circuits. The developed modeling procedures can be used for different devices and material systems.

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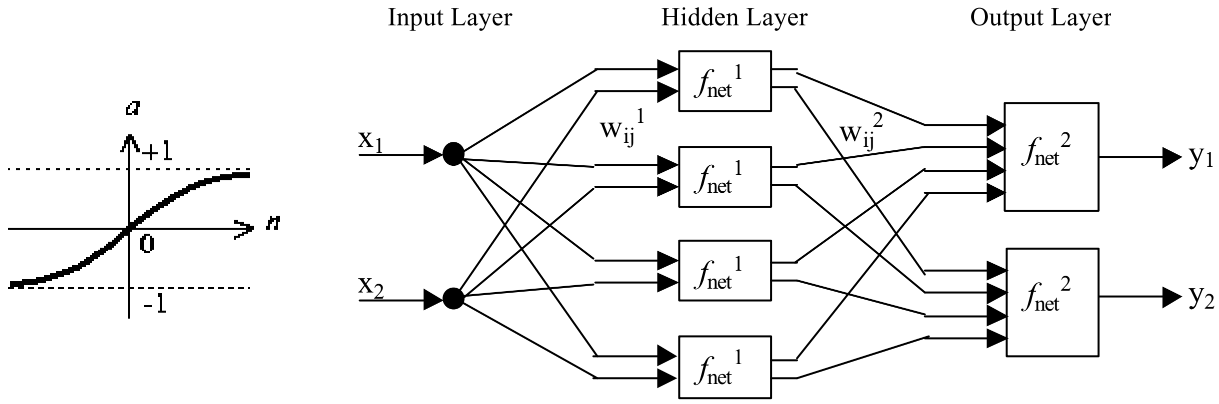
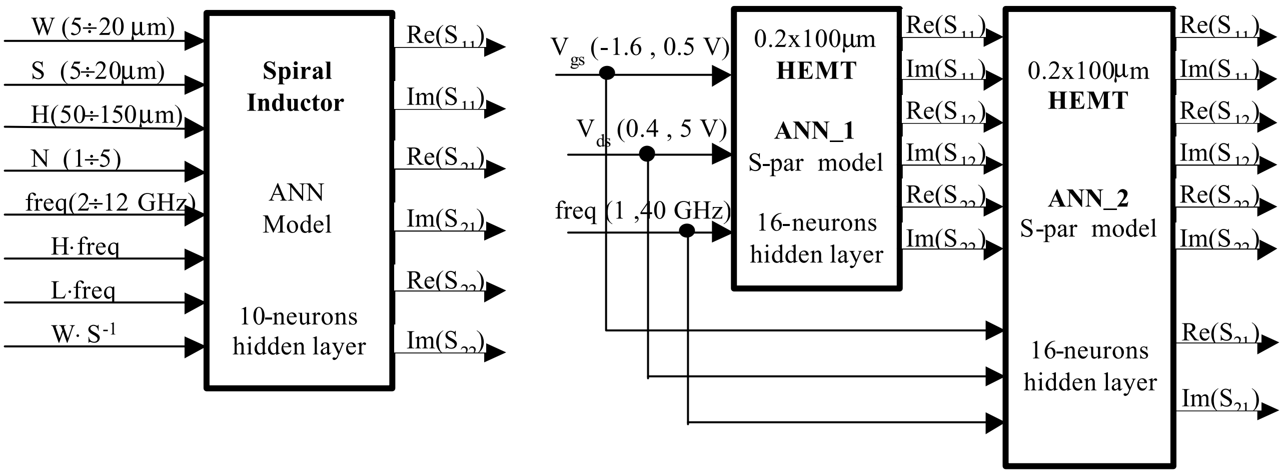


Fig.1. Example of an ANN architecture containing 2 inputs, 2 outputs, and one hidden layer with 4 neurons, with the tan-sigmoid transfer function on the left.



(a) **(b)**

Fig. 2. Block diagrams of ANN device models: a rectangular spiral inductor (a) and an HEMT device (b).

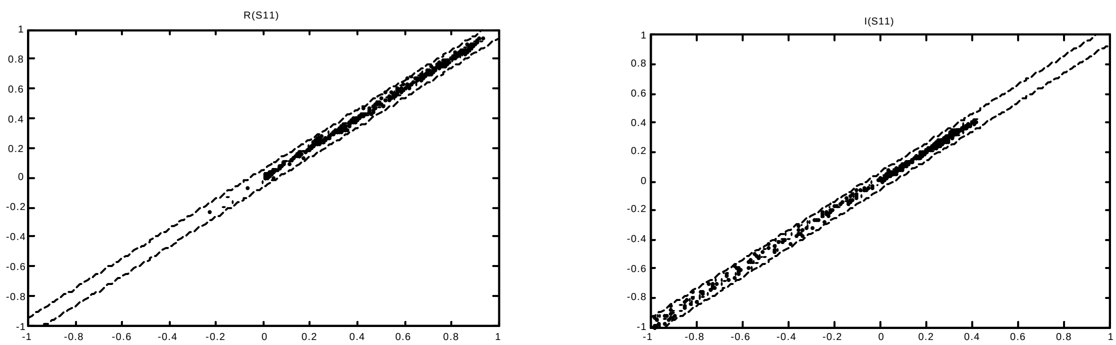


Fig.3. Scattering plots for real(S_{11}) and imag(S_{11}) of not-trained sample data from ANN-model and ECP-model of a rectangular spiral inductor.

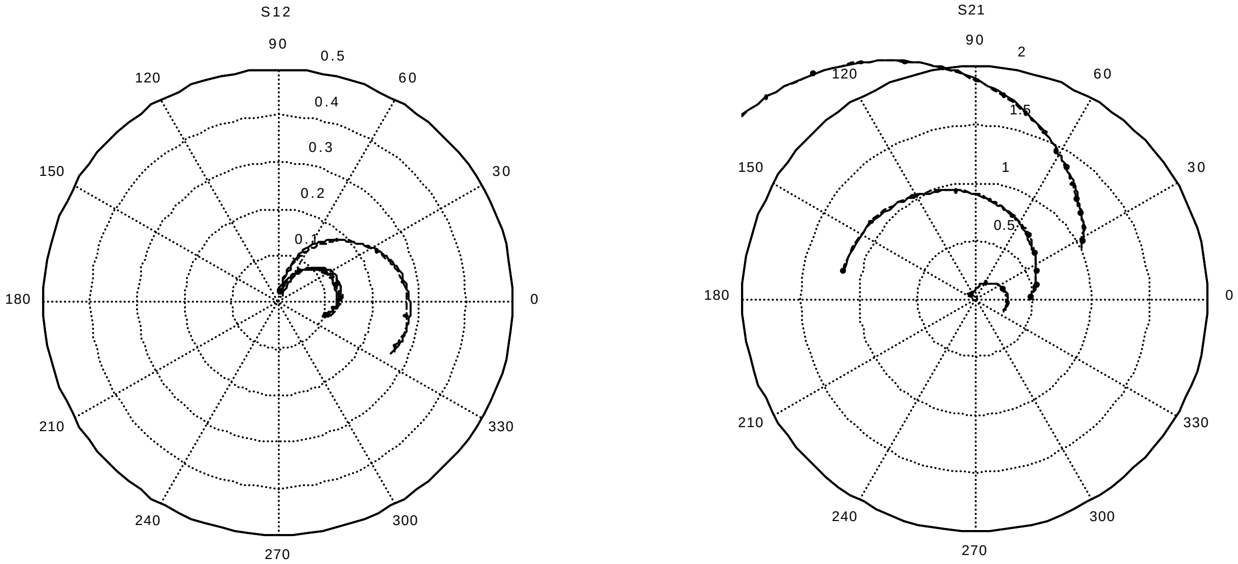
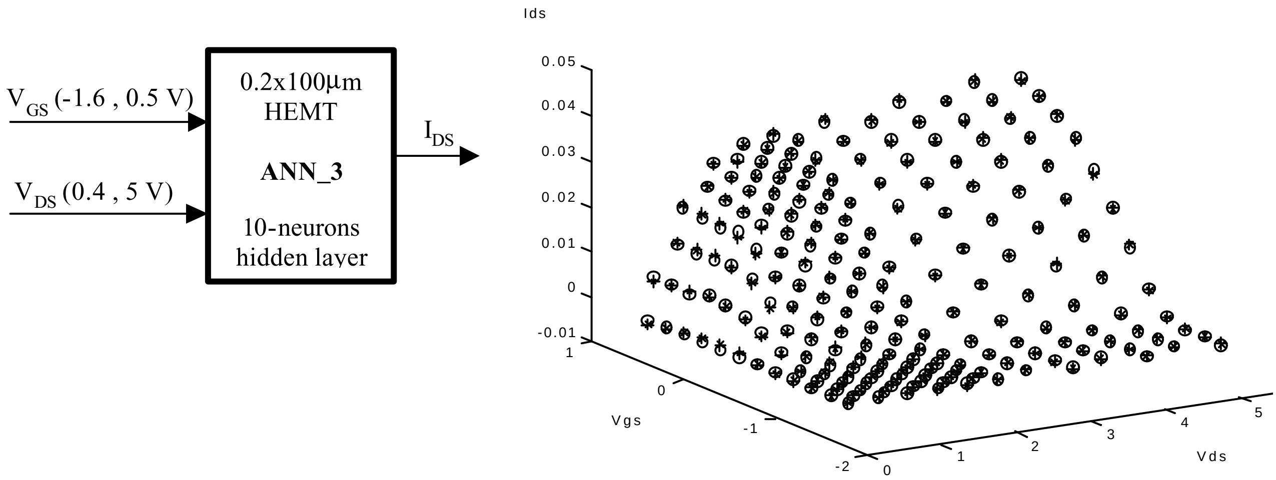


Fig.4. Comparison of ANN and measured *S*-parameters for a 100μm gate width, 0.25μm gate length δ-doped HEMT biased at (V_{GS} , V_{DS})=(-1.5,4.5),(-0.8,2.5),(0.4,2.5).



(a) **(b)**

Fig.5. I_{DS} ANN model (a) and the I-V output curves from ANN_3 and measured data for HEMT model (b).

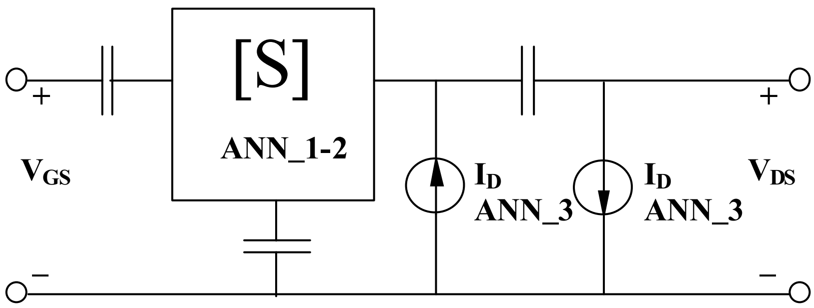


Fig.6. Small-signal bias-dependent model composed of ac bias-dependent S-param 2-port network (ANN_1-2) and dc drain current equivalent generators (ANN_3).