Dynamically Configurable pHEMT Model Using Neural Networks for CAD

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***Abstract* — A novel approach to developing CAD microwave device models is presented. Traditional CAD devices are implemented using static empirical equations to describe electrical behavior. Recently, neural networks have been used in place of empirical equations to model device behavior. This paper describes the implementation of a CAD device model that utilizes a dynamically configurable combination of empirical equations and neural networks to increase the flexibility of the model's capabilities. The model was developed for pHEMT devices but can be customized to work with other device structures such as HBTs. The framework for this model is a common-source large-signal equivalent FET circuit. With the exception of the drain current source, all of the nonlinear elements of the circuit are configurable to either empirical or bias-dependent neural network controlled components. The neural network architecture employed is based on the knowledge-based algorithm.**

I. INTRODUCTION

The application of device modeling in the microwave CAD industry is vital to the efficiency of design cycles in production environments. The traditional method of device modeling is time-intensive. It involves extensive measurement time and mathematical optimization. Popular existing device models are not as well suited for newer device technologies or highly nonlinear designs as one would like. Empirical equations do not completely model highly nonlinear behavior such as compression. One of the pitfalls of using empirical equations in models is that they do not accurately model the device behavior in all regions of operation. A logical approach would be to implement a piecewise solution to cater to individual regions of operation. Many times using a piecewise implementation leads to continuity problems. In addition, in complex simulations such as harmonic balance, it is necessary for equations to be very accurate in order to successfully converge to a solution. These conditions make the development of an empirical based model painstaking. Additionally, these models sometimes lead to simulation failures in highly nonlinear situations. Using a neural network to model the electrical behavior of a device model affords the ability to characterize nonlinear behavior statistically without the necessity of a defined empirical relationship. Knowledge-based neural networks provide additional accuracy given the knowledge of the general shape of the data being modeled. Implementation of the knowledge based neural network process into CAD device models increases simulation accuracy while reducing and simplifying development. Introducing the ability to dynamically configure the device equivalent circuit elements between empirical and neural network definitions gives the modeler freedom to tailor the model to different applications without having to redevelop it. In addition, it provides greater optimization on a particular circuit element.

COMSARE has developed a new model that combines elements that are based on both empirical expressions and neural networks, which is well suited for newer device technologies. This model is easier to develop than traditional models and is adaptable to an expansive range of applications. This adaptable neural network FET (ANNFET) model has the capability of being dynamically reconfigured by the user such that any empirically based element of the traditional FET model can be exchanged for a neural network component. A neural network component is defined by an electrical element such as a resistor, capacitor, or current source whose value is mathematically equated by a neural network.

This paper will outline the development of this model and present a comparison of its performance with a traditional empirically based CAD FET model. The organization of this paper is as follows. Section II will give a brief outline of knowledge-based neural networks and its relation to this application. Section III details the design and implementation of the model into Agilent ADS. Section IV will present an evaluation of a model that was produced and verified against measured data.

II. Knowledge-Based Neural Networks

A. *Knowledge-Based Neural Networks*

In previous work, COMSARE used the backpropagation technique to create neural networks. Now the knowledge-based (KB) technique has been instituted. There are several advantages to using the KB algorithm over the backpropagation technique. Neural networks created using the backpropagation algorithm are much more data intensive than those created using KB algorithm. This means they require a larger data space for the neural network to 'learn'. This, in turn, increases development time. Using the KB technique cuts down on training time and reduces the amount of data needed to produce a model. In addition, the KB is better able to extrapolate behavior outside a range in which it was trained. The knowledge-based neural network contains additional hidden layers: the knowledge layer, boundary layer, region layer, and normalized region layer. The knowledge layer institutes an empirical or semi-analytical equation that gives the neural network output a 'shape' that resembles the desired output. The boundary layer expands on the knowledge layer by describing a case-specific equation that the data most resembles.

B. *KB Neural Network Generation*

To adopt the KB neural network technology for device modeling, COMSARE developed software to produce weight vectors for a given data set. The data typically consisted of S-parameter and DC characteristics. This data was acquired from standard device modeling and extraction tools. The software, which let the user determine the parameters of the neural network such as number of neurodes and desired error tolerance, accepted the data in a file and trained the neural network. The weight vector was saved in a file for use in the end application, the CAD model.

The empirical equations in the knowledge layer were predetermined and implemented into the neural network generation software (NNGS). For the work done in this paper, modified versions of the Angelov [4] current and capacitance equations were used.

III. MODEL DEVELOPMENT AND IMPLEMENTATION

A. *Data Acquisition*

As a case study, two models were developed for two devices. The devices used were two GaAs pHEMTs. The Triquint Texas process was used for both devices, one sized at a gate width of 300 um and one sized at a gate width of 600 um. The devices were acquired from Johns Hopkins Applied Physics Laboratory. An extraction was performed on these devices to acquire S-Parameters and DC IV characteristics.

The DC measurements were acquired in typical fashion using standard extraction software. The hardware used was a vector network analyzer and low-power DC source monitor. The devices were swept through a drain bias range of 0 volts to 6 volts. The gate bias sweep range was from –0.9 volts to 0 volts, where –0.9 volts is the pinch-off voltage.

The S-Parameter data was acquired, again using standard extraction software, through a range of frequency and bias voltages. The biases chosen were selected from regions where the AC and DC behavior significantly changed.

The S-parameter data taken was processed by in-house software to determine the values of the parasitic and intrinsic elements.

B. *KBNN Training*

This data was used to develop the neural networks of the model elements. From the S-parameter data, a table of nonlinear gate capacitances, Cgs and Cgd, was determined with dependency on bias voltages. Likewise, the DC IV measurement data was used to produce a table of bias-dependent current values. These three entities were trained independently for about three hours each. In each case, the error tolerance was below 1e-6. Each training session produced a file of neural network model parameters. This file contained the optimized weights and the network architecture configuration parameters.

ANNFET Model Configurability		
Nonlinear Element	Empirical	Neural Network
I_{DS}	Yes	Yes
I_{GS}	Yes	No
I_{GD}	Yes	No
C_{GD}	Yes	Yes
C_{GS}	Yes	Yes

Table I – ANNFET Model Element Configurability

C. *Model Implementation*

The implementation of the ANNFET model was done in a popular microwave system design package. In order to implement the model, integration with the neural network software was achieved through a wrapper. Model implementation into the CAD design software required a description of the equivalent circuit and its voltage dependent current and charge relationships. The topology was defined by the voltage dependent admittance parameters. In typical empirical models, the nonlinear current and charge relationships are described by voltage dependent empirical expressions. In the ANNFET model, the empirical expressions are replaced by an interchangeable switching mechanism that uses either empirical expressions or neural network processing algorithms. In Figure 1, the equivalent

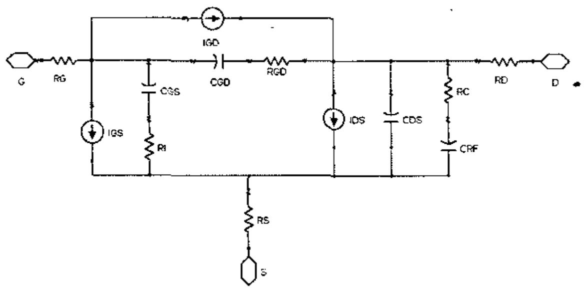

Figure 1 - ANNFET equivalent circuit model

circuit of the ANNFET mode is shown. In practice, if the user of the model desired to implement a neural network based drain-source current, a file name is supplied at the CAD environment interface. The file specifies the neural network parameters for that element. The wrapper code in the model then interfaces with the neural network software to generate the neural network topology and processes the neural network to produce the voltage dependent current. Alternatively, the empirical description of an element will take precedence if the model user selects a discrete value for that element. The code for the model automatically rearranges the topology depending on the selection of each element's type. The same process occurs for the other elements. Table I lists the configurabilities for each nonlinear element of the ANNFET model.

IV. Model Evaluation

A. *Measured vs. Model*

After the models of the two devices were implemented, simulations were done to determine how well the models could reproduce the measured data.

The simulated S-parameters match well against the measurements.

The DC IV characteristics were measured for both devices. The simulated DC IV characteristics match well against the measurements. Figure 2 illustrates a comparison of the DC IV characteristics for the ANNFET model of the 300 um device and the corresponding measured data. Very good agreement is achieved with the drain-source current, gate-source capacitance and gate-drain capacitance being modeled by the neural network. All other elements were defined by the Angelov model parameters.

B. *Comparison*

To validate the robustness of the new model, a comparison of similar metrics was performed between it and the empirical Angelov FET model.

The same measurement data from the two devices were used to extract Angelov models. This was done using in-house extraction tools. The Angelov model was also implemented into the CAD simulator. Identical simulations were performed to compare its performance to the ANNFET model.

Particular attention was paid to the comparison of the models' DC IV characteristics near the pinch-off region.

Considering that the DC IV characteristics are the most nonlinear component of the measured data it follows that it is also the most nonlinear component of the model.

It was observed that in the pinch-off region, the Angelov current expression does not model the DC IV behavior well. The knowledge-based model is much better able to the model the DC IV curves in the pinch-off region. This makes the ANNFET model very attractive for designers of Class F amplifiers as it gives more accurate current modeling in the pinch-off region. COMSARE has shown good results in the design of a Class F amplifier using this model [1]. The DC IV curve simulation of the ANNFET model in the pinch-off region is illustrated in Fig 3. Much better agreement is achieved by using the neural network to model the IV characteristics instead of the empirical equation.

V. Conclusion

A new CAD device model implementing a combination of traditional empirically based lumped elements and knowledge-based neural network elements was developed. This model can be dynamically configured to suit a variety of device structures and applications. The model was implemented into a CAD simulator and verified against two GaAs pHEMT devices. Simulated and measured data have very good agreement. The model was compared to the Angelov FET model for further validation. The simulations of the new model were just as accurate as those of the Angelov model and more so in the case of DC IV curves in the pinch-off region. The simulation accuracy combined with the ease and speed of development make the new model beneficial to the microwave CAD community.

Future development of this model will include a neural network implementation of gate diode currents. In addition, other empirical equations for the knowledge layer of the neural network may be introduced to extend its accuracy for other devices.

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References

[1] M. Reece, C. White, B. Davis, M. E. Bayne, Jr., N. Richardson, W. Thompson, II., L. A. Walker, Jr., "A Ka-Band Class F MMIC Amplifier Design Utilizing Adaptable Knowledge-Based Neural Network Modeling Techniques", *IEEE MTT-S International Microwave Symposium*, June 2003.

[2] M. E. Bayne, Jr., W. L. Thompson, II, C. White, B. Davis, M. A. Reece, N. L. Richardson, and L. Walker, Jr., "A Neural Network Model for a High Electron-Mobility Transistor," presented at *Symposium on Nano-Device Technology* Singapore, May 2002.

[3] F. Wang and Q. Zhang, "Knowledge-based neural models for microwave design," IEEE Trans. Microwave Theory Tech, vol. 45, pp. 2333 – 2343, 1997.

[4] I. Angelov, H. Zirath, N. Rorsman, "A New Empirical Model for HEMT and MESFET Devices", *IEEE Transactions on Microwave Theory and Techniques*, vol. 40, no. 12, pp. 2258 – 2266, 1992.

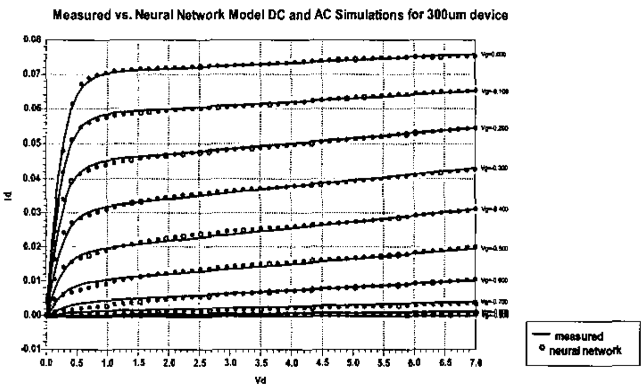

Figure 2 - Angelov model DC IV curves at pinch-off

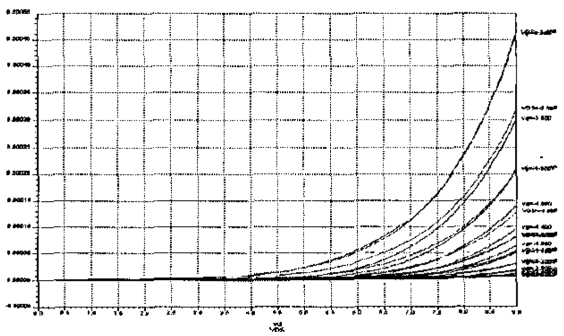

Figure 3 - ANNFET model DC IV curves at pinch-off