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Non-linear Microwave Transistor Modeling through ANNs: a Frequency-domain CAD Implementation

Chiara Ramella
Politecnico di Torino, DET
Torino, Italy
0000-0003-0634-1474

Simona Donati Guerrieri
Politecnico di Torino, DET
Torino, Italy
0000-0002-1204-7047

Simone Corbellini
Politecnico di Torino, DET
Torino, Italy
0000-0002-8746-4398

Marco Pirola
Politecnico di Torino, DET
Torino, Italy
0000-0002-5759-9697

***Abstract*—This contribution presents a black-box approach based on Artificial Neural Networks (ANNs) for the accurate and computationally efficient non-linear modeling of microwave transistors. The presented model, here applied to a MESFET test-case, adopts a feed-forward ANN to relate the harmonic components of the device's incident and reflected port waves with arbitrary harmonic loading. As such, it is conceived to be exploited for non-linear design within RF CAD tools based on the Harmonic Balance approach. The detailed implementation within Keysight Advance Design System (ADS), resorting to built-in custom modeling features, is also presented along with model validation results, demonstrating the potential of the proposed approach for fully-black-box non-linear device modeling.**

***Index Terms*—artificial neural networks, harmonic balance, microwave CAD, non-linear device modeling**

I. Introduction

The use of artificial neural networks (ANNs) for microwave circuit and device modeling is rapidly growing [1]–[3]. The distinguishing capability of ANNs to fit even very complex non-linear trends with smooth mathematical function makes them an ideal candidate for the development of accurate and efficient non-linear microwave transistor models [4]. Indeed, as microwave CAD tools commonly rely on the Harmonic Balance (HB) approach for simulating and designing of non-linear components such as power amplifiers or mixers, model regularity is essential for HB convergence.

Many examples of ANN-based models are already available in the literature: most of them are limited to DC and/or AC parameters [5] or combine ANN functions with circuit equivalents to account for several physical effects, like, e.g., trapping or thermal memory [6], [7], while few fully-black-box frequency-domain approaches have been presented so far [8]–[11]. Such models consider all the complex harmonic coefficient of the port waves as outputs, but, being conceived for power amplifier design, they consider as input only the amplitude of the incident waves at the fundamental frequency. Similarly, ANN training data often focus just on loads close to the optimum power or efficiency conditions, while a general-purpose device model should mimic the device behavior in all possible operation, even far from the one used to target a specific circuit performance.

In this work we explore an ANN-based general-purpose device model where all the harmonic components of the incident waves are used as inputs, see Fig. 1, in order to obtain a more flexible model, but still relatively easy to be implemented in CAD tools.

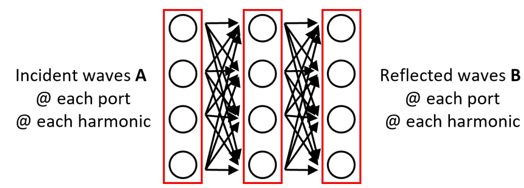


Fig. 1: Architecture the proposed ANN device model.

As a first demonstrator, a simple FET device is used, sweeping only the load impedance at fundamental frequency [12]. The extracted ANN has been implemented in Keysight ADS exploiting the frequency-domain defined device (FDD) component. The results obtained are very promising, showing excellent agreement with compact-model-based simulations.

II. ANN model extraction

Accurate device behavioral models can be extracted from measurements [13], [14] and/or physical simulations [15], [16]. However, as the aim of this work is to evaluate the modeling technique, a simple Curtice compact circuit model is adopted as a reference. Selecting a operating frequency of 12 GHz, the device is unconditionally stable and the optimum load is $(45 + j10)\,\Omega$ in class-A. Notice that the device model used has limited parasitics, since it was previously developed to fit technology CAD simulations of an almost-intrinsic GaAs MESFET [17]. For more complex models or experimental data, the need for parasitics de-embedding from training data will be explored in future work.

The ANN training data are generated through a 5-th order HB simulation of the Curtice transistor in class-A bias with fundamental load-pull sweep, see Fig. 2.

To achieve good coverage of the full Smith Chart, the amplitude of the load reflection coefficient is varied from 0.1 to 0.9 with 0.1 step, while the phase is swept from 0° to 350° with 10° step, for a total of 360 points. Short circuits are used as harmonic loads at the drain, while at the gate a source impedance of $20\,\Omega$ is adopted to ensure non-zero incident waves at all harmonics. The input power is swept from -10 dBm to 30 dBm using 100 points with non uniform distribution: a finer step is used at high power where the

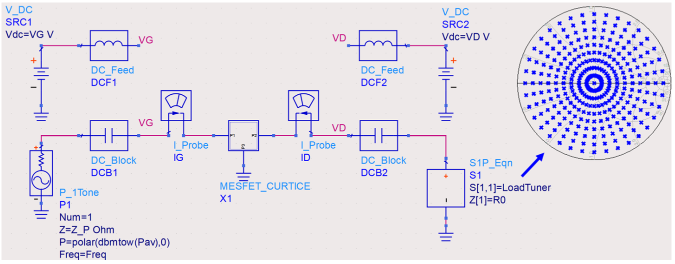


Fig. 2: Generation of the ANN training data from the Curtice model and a load tuner spanning the whole Smith Chart.

behavior is significantly non-linear due to compression. In this work, the same power sweep points are used for all the analyzed loading conditions, leading to significant difference in the degree of compression achieved. The real and imaginary parts of the complex harmonic coefficients of the incident and reflected port waves at each of the 36 000 points are collected to form the dataset for the ANN training. The data are normalized in the interval $[-1, +1]$, to compensate for the wide variations in the harmonic wave amplitudes.

Although EDA tools (e.g. Keysight Advanced Design System) are now starting to offer proprietary Python functions to extract feed-forward networks from electrical data [18], we prefer to use an in-house software [12] with advanced features to identify the ANN akin to the one shown in Fig. 1. To keep the ANN structure simpler, two separate ANN networks are used, each one having all the $\mathbf{A}$ waves as inputs and the $\mathbf{B}$ waves of the gate and drain ports as outputs, respectively. We have also enforced an identical structure for the two ANN's. Different number of neurons and layers have been investigated: the best performance has been obtained with a fully connected network including 3 hidden layers of 14, 24 and 15 neurons respectively, a sigmoid activation function and bias input in each layer [12]. Including the input and output layers, each ANN has 128 trainable neurons.

III. ANN validation in Keysight ADS

In [12], we demonstrated that the proposed ANN model can be seamlessly used as a Curtice model replacement within an in-house HB circuit solver. However, for a device model to be of practical interest for microwave designers, the possibility to implement it within commercial CAD tools is fundamental. Keysight ADS is extremely helpful in this sense as it provides built-in user-defined devices for the definition of custom non-linear models, in either the time domain (symbolically-defined device, SDD) or in the frequency domain (frequency-domain defined device, FDD).

The FDD is the ideal component for developing non-linear behavioral models working in an HB environment, also for ANN development [19], as it enables the user to implement model equations relating port current and port voltage spectral values through algebraic expressions. Being our model based on port waves, in the form

$$\mathbf{B} = f(\mathbf{A}) \tag{1}$$

the most straightforward way to implement it with an FDD is to map incident and reflected port waves into, respectively, port voltages and currents as shown Fig. 3. The circuit source and load impedances should thus be dimensioned as reflection coefficients

$$\begin{aligned} \mathbf{V_{1,2}} &= -Z_{S,L}\mathbf{I_{1,2}} \\ \mathbf{A_{1,2}} &= \Gamma_{S,L}\mathbf{B_{1,2}} \end{aligned} \Rightarrow Z_{S,L} = -\Gamma_{S,L} \tag{2}$$

while the input source voltage must be sized to give the same available input power P_{av} level of the 1-tone HB port adopted with the Curtice model. Assuming that the latter has a series impedance Z_P we have $P_{av} = |V_P|^2/4\Re\{Z_P\}$ thus

$$\begin{aligned} \mathbf{V_1} &= \mathbf{V_S} - Z_S\mathbf{I_1} \\ \mathbf{A_1} &= \Gamma_S\mathbf{B_1} + \mathbf{B_P} \\ \mathbf{B_P} &= V_P\frac{\sqrt{R_0}}{Z_P+R_0} \end{aligned} \Rightarrow \mathbf{V_S} = \mathbf{B_P} = \frac{2\sqrt{R_0\Re\{Z_P\}P_{av}}}{Z_P+R_0} \tag{3}$$

where R_0 is the normalization resistance. Similarly, the DC supply voltages at the two ports must be set to $V_{G,D}/\sqrt{2R_0}$, with series impedances of $1\,\Omega$ corresponding to $-\Gamma_{\text{short}}$, to properly set the desired gate and drain DC voltages.

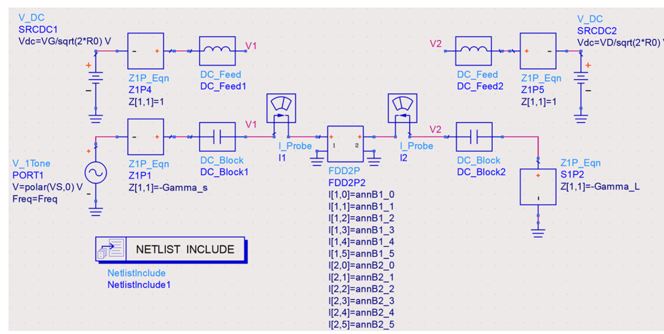


Fig. 3: FDD implementation of the ANN model within ADS.

The equations defining the ANN function f in (1) are included as a *Netlist* file, created from the extracted ANN by an ad-hoc defined automatic routine. Fig. 4 shows in more detail how the model is practically implemented in the netlist.

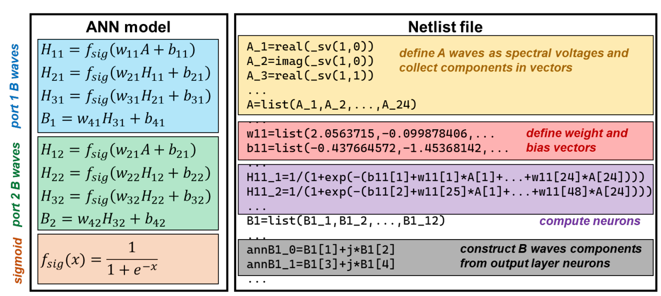


Fig. 4: Translation of the ANN model into an ADS netlist.

The ANN model has been tested on several different fundamental loads, not included in the training load-pull sweeps, see Fig. 5. The results, compared to circuit-level simulations with the Curtice model show an excellent agreement in terms of waveforms (Fig. 6) even in harsh compression and widely different operating conditions, proving that the whole harmonic content is well captured by the model. Fig. 7 reports typical device performance of interest for power amplifier applications: the results are also good, apart from a slightly overestimated small-signal gain, meaning that the ANN model can be profitably exploited for amplifier design. Further ANN generalization, allowing for inclusion of harmonic source- and load-pull data at different bias (e.g. class B), and the investigation of the convergence robustness in the Harmonic Balance environment is currently under investigation.

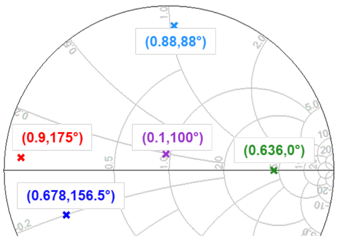
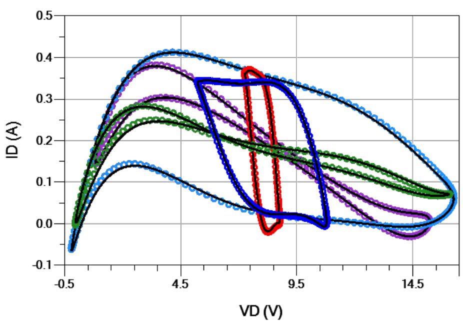
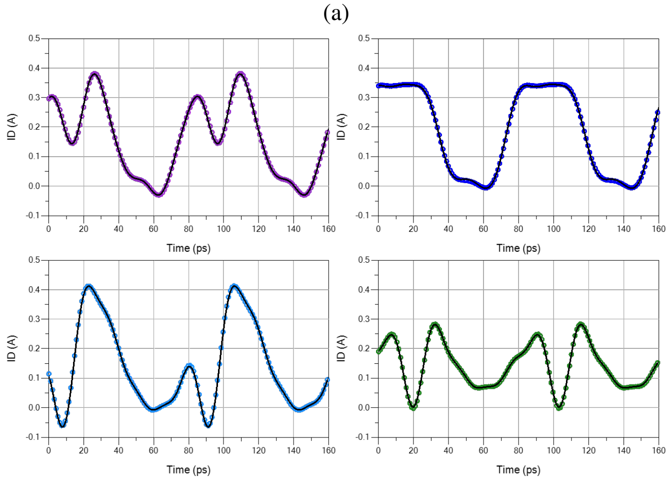


Fig. 5: Selected test loads.



(a)



(b)

Fig. 6: Dynamic load lines (a) and current waveforms (b): ANN model (symbols) compared to Curtice model (black solid). Symbol color indicates the loads according to Fig. 5.

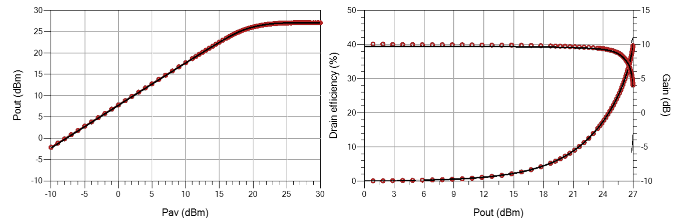


Fig. 7: Device large-signal performance on the optimum load $Z_L = (45 + j20)\,\Omega$: Pin-Pout curve (left) and power gain and efficiency as a function of output power (right).

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