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Modeling of HEMT Devices Through Neural Networks: Headway for Future Remedies

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***Abstract*—Small-signal and large-signal modeling of high electron mobility transistors (HEMTs) are developing day-by-day where accurate model extractions rely on characterizing the behaviour of transistors appropriately. Determining the suitable and optimal model structure with component values is not straightforward and requires significant effort especially at high frequencies. This modeling task is becoming more sensitive to numerical errors and convergence issues and needs careful consideration. Recently, neural networks (NNs) prove their beneficial applications in the radio frequencies design leading to accurate modeling. In this framework, this paper devotes to provide the comprehensive literature review around the various methods employed to modeling HEMT transistors through NNs. By referring to this review, radio designers can get a general view of HEMT modeling in one glance and can select the most suitable scheme for their applications.**

***Index Terms*—modeling, high electron mobility transistor (HEMT), large-signal modeling, neural network (NN), small-signal modeling.**

I. Introduction

Wireless communication systems for fifth and sixth generations (5G/6G) are developing day-by-day, leading to improved data transfer [1]. The deployment of the radio frequency (RF) front-ends typically require microwave and mm-wave devices from enabling technologies. The GaN technology is preferred to silicon, due to its higher operation temperature, high breakdown electric field and electron saturation velocity [2]. Dedicated devices such as the high electron mobility transistors (HEMTs) based on wide bandgap semiconductors such as GaAs or GaN represent the state of the art for microwave applications [3], typically targeting 5G and beyond communication systems, vehicle networks [4], ultra wideband radar systems and space [5]. Recently, these devices have shown interesting applications also in heterogeneous engineering fields, including the medical and health areas (e.g. biosensing for COVID-19 [6]).

High power amplifiers (HPAs), used in the transmit chain of wireless communication systems, still represent the core of the applications for GaAs and GaN HEMTs [3], [7], [8]. HPAs design typically starts with the selection of the active devices (HEMTs) and develops by configuring the matching networks, sizing the passive structures by selected design parameters [9], [10]. Accurate HEMT modelling plays a crucial role in microwave design [11], [12], and poses significant challenges especially since GaN HEMTs are still undergoing significant process and structure optimization, to overcome the relative immaturity of the GaN technology [13], [14]. Substrate engineering is also actively investigated, where Silicon, SiC or even diamond systems are used [15], [16], making transistor modelling even more involved.

Both small and large-signal GaN HEMT models, including noise and frequency conversion, are required for accurate circuit design. Besides TCAD physics-based analysis [17], equivalent-circuit based (compact) models are the first choice due to their ease of implementation into circuit simulators. At high frequencies, though, parasitic effects and low frequency dispersion due to trap dynamics and thermal effects make the circuit identification and parameter extraction more difficult [18], [19]. Behavioral models are also popular for nonlinear HEMT modelling, e.g. using polyharmonic distortion, X-parameters [20] or the Padé model [21], but their validity relies on the availability of large characterization data and the extrapolation capability is poor. The model extraction also requires significant numerical effort for optimization.

At the physical level, HEMT transistors are analyzed by Technology Computer Aided Design (TCAD) tools, e.g. Sentaurus Synopsys [22]. Despite physical models allow to speed up the device fabrication process, they are extremely numerical intensive, and not suited for circuit design. On the other hand, they provide the ideal platform to generate cheap and accurate surrogate data for the development of behavioral models [20] or artificial neural network based models [23], in substitution to expensive and complicated experimental campaigns [24].

In fact, artificial neural networks (ANNs) seem to be the ideal framework [25] to retain the high accuracy of device characterization or physical analysis with the numerical efficiency required in circuit simulation [26], [27]. Once trained with data generated from simulation or measurement platforms, ANNs virtual models can replace electromagnetic (EM)/physical models in the whole design, accelerating the circuit design.

A vast set of ANN-based HEMT modeling or, more in general, ANN-aided GaN circuit design, are present in the literature, making the overall scenario very crowded. It is becoming increasingly difficult to identify and classify the ANN approaches and modeling solutions. This paper provides a comprehensive review over the diverse surrogate techniques in the recently published literature, highlighting the pros, cons and challenges. This research aid designers in selecting the most suitable modeling approach for their applications.

This comprehensive review is organized as follows: Section

II provides a general descriptions of the adopted neural networks. Section III summarizes the various methods employed for HEMT modeling with ANNs. Finally, Sec. IV concludes this manuscript.

II. ANN Investigation Modelling in a Nutshell

The intelligent-based networks have various subsets as presented in Fig. 1. Due to the requirements of various modeling, the suitable network type can be selected. As depicted in Fig. 1, machine learning (ML) includes any type of computer program and it is subset of artificial intelligent (AI) that can be fitted to the human interference. Deep learning (DL) is placing inside of ML where it uses the neural networks for matching to the learning process of the human brain. Additional specifications of each type are summarized in the appointed figure.

There are various kind of ANNs namely: multilayer perceptrons (MLPs), knowledge-based neural networks (KBNNs), and deep neural networks (DNNs) that are employed for various microwave applications such as: microwave filter designs [28]–[32], microwave antenna designs [33]–[35], RF amplifier designs [36]–[38], digital predistortion (DPD) [39], [40]. ANN with space mapping optimization method are employed e.g. in [19], [41] for learning electromagnetic (EM) and physics behaviour of RF designs. In this paper we focus on transistor modeling, which is the aim of Sec. III.

DNNs are the most widely used structures, which can be furhter subdivided into classes.

- Deep neural networks (DNN);
  1) Deep multilayer perceptrons (MLPs) [42]
  2) Convolutional neural network (CNN) [43]
  3) Deep belief network (DBN) [44]
  4) Knowledge-Based Neural Network [45]

A typical feature of microwave models, both at the device and circuit level, is that they must represent widely different data, ranging from DC, small-signal and multi-tone (usually represented in the frequency domain) or modulated signals (usually in a mixed time-frequency domain). This leads to exploiting a vast set of possible ANN structures. Feed-Forward Neural Networks are the simplest solutions usually adopted to model DC or frequency domain responses that are not adaptive in time. More complex ANN structures, such as the recurrent or Long Short-Term Memory ANNs are more apt to be trained with time-domain wave-forms or to be adaptive with the environment conditions (e.g. for energy-harvesting applications). The following scheme provides some examples of ANN structures proposed in the recent literature in this scenario.

- Feedforward Neural Networks (FFNNs) for passive and active circuit modeling, e.g. in DC or in the frequency domain [46], [47];
- Time-domain ANNs for time domain or mixed time-frequency domain modelling
  1) Dynamic neural networks [48]
  2) Recurrent neural networks (RNNs) [44]
  3) Time-delay neural networks (TDNNs) [49]
  4) Long Short-Term Memory (LSTM)-based DNN [36], [50]

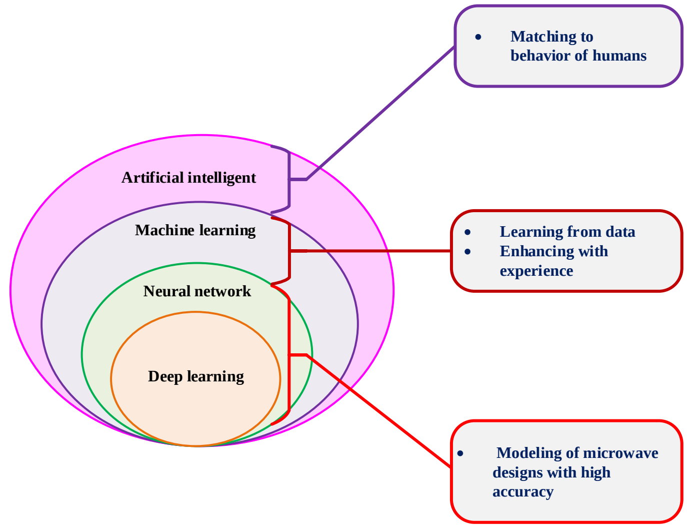

Fig. 1. AI, ML, and DL sub-sections.

Any engineer can develop the ANN by proper training, which can be done following the steps as below:

1) Determining the specifications of input layer;
   - each microwave design has its own characteristics. For example, they can be design parameters or input data of circuits [33], [36], [51], [52].
2) Providing the hyperparameters of ANN;
   - Hyperparameters include number of hidden layers and number of neurons in each layer [53].
3) Defining activation function with loss function [54];
4) Concluding the specifications of output layer;
   - The final layer includes characteristics that are targeted to be predicted [55].

III. HEMT Modeling Techniques

This section devotes to summarize the methods and techniques used for modeling the active devices as HEMT transistors. In the recently published studies, various methods are reported for HEMT small-signal and large-signal modeling. Accurate analytical expressions can be used to develop corresponding compact models [11]. Analytic functions are not an effective modelling approach since they require significant effort for finding and fitting the model parameters depending on the device technology [56], [57]. To tackle this problem, artificial intelligent (AI) becomes a promising solution as it provides the relationship between the input and output data [25]. Table I at the end of this paper, presents the comprehensive view around these methods that are based on the the neural networks.

The main advantage of the ANN is to deal with large amount of data and to find the optimal solutions for the real-time engineering applications [58]. The construction of the ANN can be varied mostly based on the type of feedback,

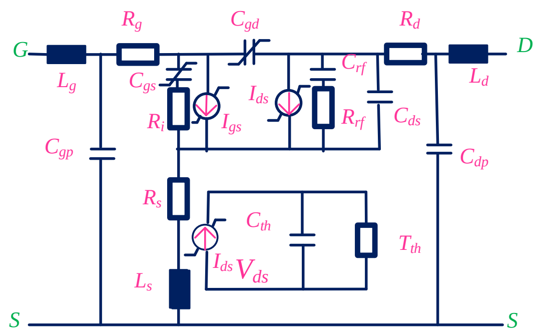

Fig. 2. Large signal HEMT equivalent circuit, used e.g. in [60].

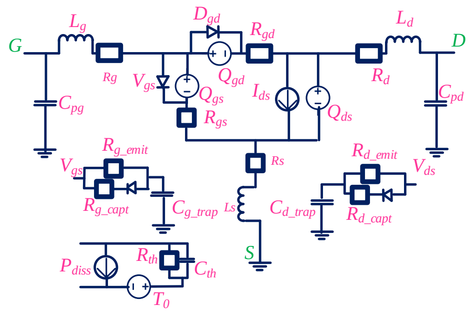

Fig. 3. Improved Large-signal model of GaN HEMT, as in [61].

number of neurons and the number of layers. Following presents these varied types and methods.

A significant amount of works deal with equivalent circuit models [59]: a typical example is the one reported in Fig. 2, where the thermal effects are modelled by means of a simple RC thermal circuit.

Additional RC blocks can be added to model trap effects: separate blocks mimic the emission and capture trap characteristic times. Nonlinear charge components replace in this case the nonlinear capacitances, as shown in Fig. 3.

One of the benefits of the ANN is to be substituted into the equivalent circuit of transistor to improve the model accuracy. In fact, selected parts of the equivalent circuit (e.g. the controlled current source for I_{DS} or the thermal or trap circuits) can be replaced by a trained neural network, to generate global surrogate models that show high accuracy over a wide range of operating conditions and are prone to be implemented into circuit simulator since the ANN activation functions are usually continuous and well behaved functions (tanh).

Starting with the IV device characteristics, the most simple ANN implementation is by substituting the drain current generator by a Feed-Forward Neural Network (FFNN) with a single layer, as in Fig. 4: this structure (with three neurons) is the one selected in [62] to model the isothermal drain current.

The ANN can also account for thermal and trap effects. In [60], a feedback-based ANN is used for modeling the current-voltage (IV) characteristics of GaN HEMT: the input layer features are V_{GS} and V_{DS} while the feature of the output layer is I_{ds}, as shown in Fig 5. Notice that in this case temperature feedback in the electrical circuit is substituted by the feedback in the ANN structure. On the other hand, in [62] temperature is used as an extra input of the FFNN of Fig. 4, while the

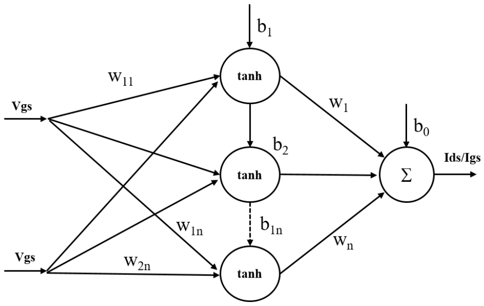

Fig. 4. Simple FFNN for the current generator (gate or drain).

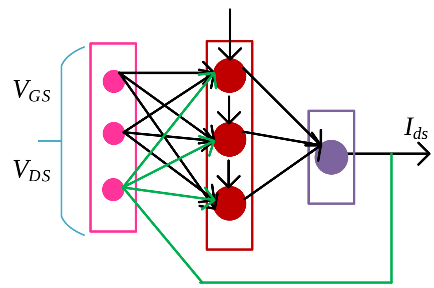

Fig. 5. ANN method for modeling the self-heating specification in [60].

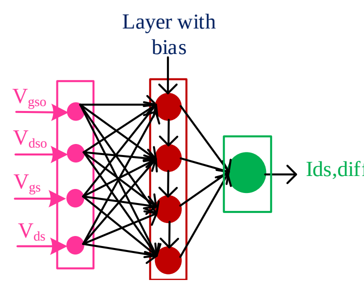

Fig. 6. ANN structure presented in [62] to model the trap induced dispersion. The ANN is used as a part of the global ANN in the GaN HEMT modeling.

thermal feedback is modelled by a dedicated ANN.

Again in [62], separate ANN models are used for providing the characteristics of GaN HEMT in terms of intrinsic, self-heating-induced and trapping-induced nonlinearities. The example of the ANN used for trap effects on I_{ds} is shown in Fig. 6. Here, the inputs are not only the gate and drain static voltages, but also the quiescent points used in pulsed IV characterization. Compared to conventional RC trap models, ANNs can be optimized on a wider set of quiescent conditions, also in conjunction with thermal effects, see again [62], yielding more accurate HEMT modelling.

Extensions of [62] exploit DNN FFNN with 2 hidden layers. Furthermore, various advanced optimization techniques have been proposed and compared. In [63], a large signal HEMT model at high frequencies is presented where the temperature dependency is accounted for by memory-less ANN blocks coupled to resistor-capacitor (RC) filtering blocks. The dynamic trapping effects are presented by the RC circuits in the gate and drain of HEMT transistor. Hybrid Genetic algorithm (GA)-ANN, particle swarm optimization (PSO) with Support Vector Regression (SVR) and Gaussian Process Regression (GPR)-Based Approaches are used.

In [61] a different modelling approach for trap effects is used: two extra inputs to the FFNN represent the ”status”

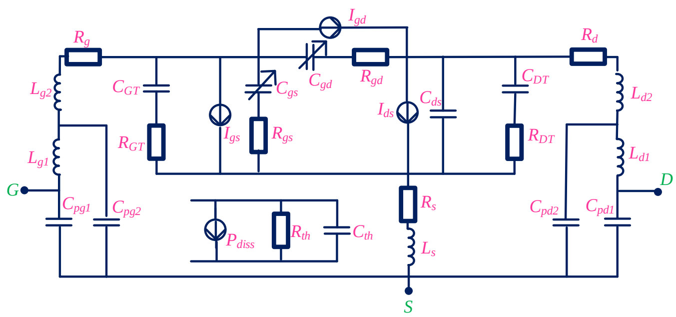

Fig. 7. Proposed equivalent circuit topology in [65] for AlGaN/GaN HEMTs.

(potential) of gate and drain traps [18], paying attention to the gate and drain lag effects. In the generated model, the extrinsic parasitic parameters are achieved based on the artificial bee colony algorithm. For this case, the ANN is constructed to estimate the drain current values that are achieved from the I-V measurements.

In [64], an accurate consistent gate charge model is presented for modeling the GaN HEMT, again through a FFNN. The circuit parameters are extracted through multi-objective Gray-Wolf optimization (GWO) and the neural network is used for modeling the bias and temperature-dependent gate charges.

Further extending the above concepts, ANNs are employed in [65] for modeling HEMTs of AlGaN/GaN technologies affected by significant buffer-related trapping effects. Such effects are especially difficult to model with analytic models. Fig. 7 presents the proposed topology of the equivalent circuit to include these effects. Here also, the use of ANN is preferred to identify the I_{ds} model as well as the trap and thermal models. First, a hybrid small-signal parameter-extraction method is used to extract the parasitic parameters. Then, the ANNs are introduced to describe trapping, breakdown, and self-heating effects. Finally, a new empirical equation is used for modeling the low-frequency dispersion, using the S-parameters to verify the buffer trap model.

Turning to small-signal models, the key elements to be extracted for accurate comparison with scattering parameters are the nonlinear capacitances or charges. In [66], ANN models for the gate and drain charges are performed with particle swarm optimization and it is verified using S-parameters.

In another study based on the genetic algorithm (GA) [67], temperature-dependent small-signal modeling methods are presented and verified with the S-parameters. Fig. 8 presents the structure of ANN used, with the input layers include four specifications of V_{GS}, V_{DS}, T, and f, and the output layer presents the real and imaginary parts of S-parameters.

Alternatively, for electrothermal small-signal modeling, [68] employs the scheme represented in Fig. 9, which includes various neural networks to represent S-parameter in terms of magnitude and phase. Temperature dependency is represented here by dedicated blocks cascaded to the ANNs.

Gray-Wolf optimization (GWO), inspired by grey wolves

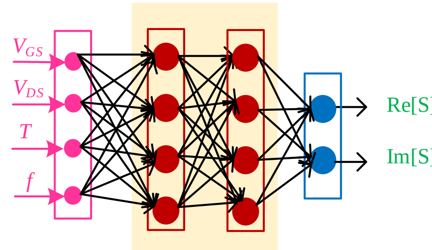

Fig. 8. Conceptual view of trained neural network for modeling the temperature dependent small-signal of GaN HEMT in [67].

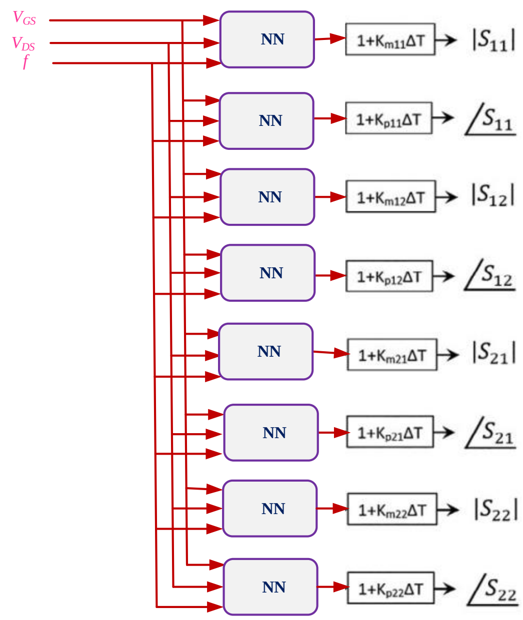

Fig. 9. NN presented in [68] for predicting the S-parameters in terms of magnitude, phase and temperature.

[69], is nowadays extensively used for modeling the GaN HEMT. Interestingly, the widespread of optimization methods needed for ANN training, has also fostered new and robust optimization methods to extract circuit elements of conventional equivalent circuits (Figs. 2-3). In Ref. [70], distributed parasitic capacitance are optimized with the GWO method in which the fitness function is maximized in terms of S-parameters, achieved through simulation and measurement. In [71]–[73], GWO method is employed for determining the values of components in HEMT model.

The above discussion has focused on equivalent circuits: these models, once made bias and temperature dependent, turn out to be also accurate and flexible large-signal HEMT modeling approaches. Despite this, more accurate, dedicated large-signal models (LSMs) are often required for HEMT models to be used in power amplifiers with large compression, self-heating and wideband modulated signals.

HEMT behavioral models are black-box flexible and general models that can fit wide sets of experimental data, including the time domain waveforms. As such, they are especially suited for large-signal modelling of devices operated with harmonic loads or fed by amplitude modulated wideband signals. Behavioral models are usually extremely difficult to

TABLE I
SUMMARY OF VARIOUS METHODOLOGIES USED FOR MODELING THE GAN HEMT THROUGH NEURAL NETWORKS

Ref.	ANN type / optimization method	Kind of application
[60]	Feedback-based ANN	Modeling the IV characteristics
[63]	GA-based ANN and PSO-based SVR	Large modeling of HEMT and considering the dynamic trapping effects
[65]	LSM-based ANN	Large-signal modeling with a hybrid small-signal parameter-extraction
[70]–[72]	GWO method	Achieving the optimal values of HEMT's design parameters
[62]	GA-based ANN	IV characteristic and electrothermal modeling of HEMT
[67]	GA-based ANN	DC modeling of HEMT and presenting HEMT with S-parameter
[68]	Feedforward-based ANN	Presenting HEMT with S-parameter in terms of magnitude and phase
[61]	ANN-based bee colony algorithm	Large signal electrothermal model with IV characteristics
[64]	Feedforward ANN with GWO method	Modeling the bias and temperature-dependent gate charges

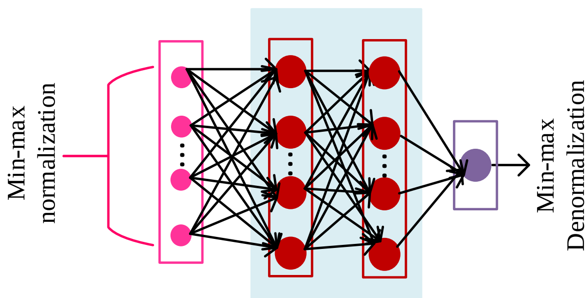

Fig. 10. The method presented in [81] for generating ANN where the input layer include incident waves and auxiliary variables to describe memory (time samples) and the output layer is the discrete time-sampled reflected wave. Input and output data min-max normalization is used.

extract, despite recently space mapping techniques have been proven successful [74]. A Wiener-type behavioral model based on ANN is reported in [48]. Behavioral models are also tightly related to the kind of measurement used for fitting. The DynaFET model [75] from Keysight exploits Nonlinear Vector Analyzer data to directly extract analytic expressions for Id and Qd as a function of the on temperature, two trap states, and instantaneous terminal voltages and implements them into the circuit simulator ADS by means of ANNs. X-parameters, also introduced by Keysight [76], are also a successful behavioral model for HEMTs, but they require large data files. In [77], X-parameters have been successfully coupled to ANNs to improve numerical efficiency. Large signal S-parameter based models are reported using real valued FFNN in [78]. Ref. [79] presents a review of large-signal ANN HEMT models based on load-pull systems. In particular two support vector regression (SVR) machines take incident waves (real and imaginary parts) as in input and return scattered waves as output. Time domain approaches including memory through waveform time samples are e.g. presented in [80]. The optimization is done based on the Z-parameter measurements. Space mapping is employed e.g. in [41] while in [19] for learning electromagnetic (EM) and physics behaviour of RF designs.

To be considered in the circuit-level, in [81] the multi-tone distortion based on time-domain is presented for modeling and predicting the transistors used in amplifier stages. For this case, the ANN is implemented and is used in a harmonic balance simulator (Keysight ADS). The general structure of the presented ANN is described in Fig. 10, as well.

IV. CONCLUSION

Designing RF circuits especially at high frequencies, is a challenging task and requires accurate modeling. The HEMT transistors are typically used in the design of amplifiers and have strong frequency dispersion. For this case, recently various modeling methods have been presented leading to consider the trapping effects of transistors. This paper devotes to provide a general view on various employed methodologies for providing small-signal and large-signal equivalent models of HEMT transistors. Due to the beneficial aspects of the ANN, this paper describes the physical knowledge and parameter extractions of HEMT transistors that are based on ANN network. Any designer by considering the various presented methods in modeling the HEMTs, can get benefit for their problems.

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