Temperature Dependent SVR and ANN Based I-V Models for GaN HEMTs

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***Abstract*— In this paper, an efficient Support Vector Regression (SVR) and Artificial Neural Network (ANN) based IV models for Gallium Nitride High Electron Mobility Transistors (GaN HEMT) is proposed. The modeling approaches are applied on pulsed IV measurements of a standard size 1-mm GaN HEMT at four different ambient temperatures of 25, 40, 55, and 70 ˚C. A non-parametric based Bayesian optimization is exploited to optimize the hyper parameters of SVR & subsequently improve its prediction capability. The two models were evaluated it terms of the mean squared error and their ability to accurately predict the IV characteristics. An excellent agreement with the measurement has been obtained over the entire operational regions of the transistor. Analytical formulas for the drain current based on both models have been provided and it can be easily implemented in standard CAD software.**

Keywords—Artificial Neural Network (ANN), GaN HEMT, large-signal-modeling, Support Vector Regression (SVR).

I. Introduction

The increase in power consumption is estimated to reach 40% in the next 20 years [1]. The number of wireless connections is increasing rabidly due to the enormous development of wireless technologies. This stresses the need for advanced transistor that can efficiently operate at high power and frequency. GaN HEMT as a wide-band gap semiconductor is an obligatory technology to improve energy efficiency and the quality of future communication systems. GaN HEMTs provide superior properties and improvements compared to silicon or gallium arsenide overcoming the limitations of these technologies to work at higher breakdown voltage, higher saturated electron drift velocity, and higher thermal conductivity [2]. GaN HEMTs can also operate in higher temperature that is applicable for high voltage devices, which allows its use in power electronics. Power electronics provide optimal electric power, which will reduce electric consumption and electricity expenses [2]. Moreover, GaN HEMTs works as a power amplifier that has the advantage of working in high frequencies, wide signal bandwidth, and wide channel bandwidth, which helps in future communication like 5G technology [3]. Furthermore, the power amplifiers that are based on GaN HEMTs reduce the equipment used for cooling and electricity consumption [4].

Building a model is a crucial step in understanding the behavior of a system or device in different situations that allow the designer to investigate the device in more detail and look for the device's suitability. GaN HEMT has the issue of charge carrier trapping and thermal effects. Both result in trapping and thermal induced memory, which impact the nonlinear behavior of the device especially for power amplifier design applications. In general, thermal effect currently represent the main modeling issue especially for high power transistors. The temperature increases the channel resistance considerably, specifically for short channel devices. As temperature rises the scattering is increased because of the intensified vibrations of the lattice, which reduces electron speed thus decreasing the I_{DS} [5]. This of course deteriorate the RF characteristics of the amplifier including output power, gain, and efficiency. Pulse IV measurement represent an optimal technique for characterizing the trapping and thermal effect. The pulsed IV at cold quiescent bias voltages (zero power dissipation) represents isothermal measurement that could be used to depict the drain current's dependency on the temperature [6].

A Plethora of research articles have been reported to address various modelling techniques of GaN HEMT [5], [7], [8], [9], and [10]. One of the published works such as in [8] presents electrothermal modeling for the GaN devices based on breaking down the nonlinearity of the transistor into intrinsic trapping-induced and thermal-induced nonlinearities using Artificial Neural Networks (ANN), and genetic algorithm (GA). Another paper [9], handled the electrothermal modeling of the GaN HEMTs using ANN only, taking into consideration the trapping effects. A different type of modeling was implemented using TCAD simulation tool which took source/drain access resistances and their temperature dependence into consideration [5]. A different paper modeled the GaN S-parameters using decision tree classifier, and Bayesian hyper parameters optimization techniques [10]. Another work published in [7], addressed temperature modeling of I-V characteristics of GaN transistors using three different machine learning techniques: ANN, Support Vector Machine (SVM), and Decision Tree Classifier (DTC). However, the proposed models have been applied on DC IV measurements of small 40 μm device. The implemented measurements cannot be considered as isothermal to provide accurate characterization for the drain current's temperature dependence. Also, the device is small and does not represent the typical size of this power transistor.

In this paper ANN and Support Vector Regression (SVR) based models are developed and applied to simulate the bias and temperature dependence of the GaN HEMT IV characteristics. The main contributions of this paper are: (i) using SVR instead of SVM, which is simpler and fits our modeling problem; (ii) both ANN and SVR models have simple topology, which simplify their implementation in Computer-Aided-Design (CAD) software; (iii) true isothermal puled IV measurements at zeros quiescent voltages are utilized to characterize the temperature dependency; (iv) the modeling procedures are demonstrated on standard size of 1-mm GaN HEMT; (v) the SVR modeling is improved by using Bayesian optimization, which according to authors knowledge has not been widely used to address this type of problem.

II. Transitor Physics and Characterization

Fig.1. depicts the epitaxial structure of the examined devices. The AlGaN/GaN HEMT structure was grown on SiC 2"-wafers using MOCVD technology [11]. Initially, to do away with the threading dislocations in the GaN buffer layer, the epitaxial growth structure embarks by depositing 500 nm thick AlGaN layer on the substrate. These dislocations arise

due to the lattice mismatch between GaN and SiC layers. Afterwards, a 2.7 µm thick highly insulating GaN buffer layer is deposited to obtain less background carrier concentration and as a result surge the electron mobility in the above unintentionally doped layers. The buffer layer is followed by a 3 nm Al0.25Ga0.75N spacer, 12 nm Si-doped Al0.25Ga0.75N supply layer (5x1018 cm-3), and 10 nm Al0.25Ga0.75N barrier layer. The spacer layer is included to reduce the ionized impurity scattering that depreciates electron mobility in the 2DEG. The spontaneous and piezoelectric polarization of these Al0.25Ga0.75N layers on top of the buffer form a 2DEG at the AlGaN/GaN interface.

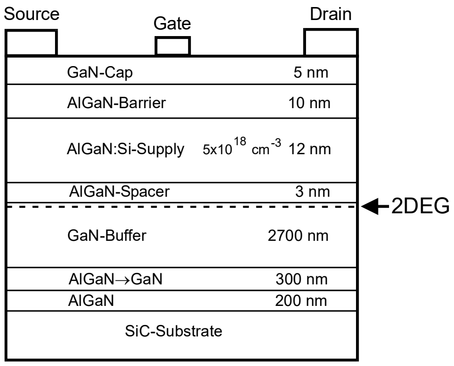

Fig. 1: Epitaxial structure of AlGaN/GaN HEMT on SiC substrate.

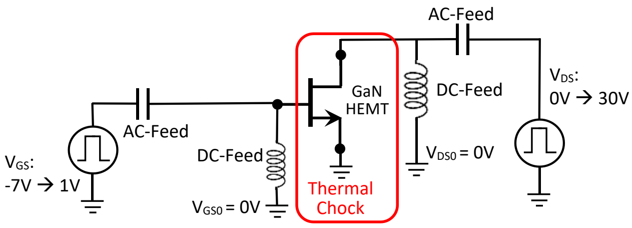

Fig. 2: Pulse IV thermal measurements set-up.

The device is characterized using the set up presented in Fig. 2. The quiescent voltages V_{DSO} and V_{GSO} are zero (connected to ground through feeding inductors). To guarantee the abort of additional trapping and self-heating due to quiescent power, the device is kept at zero values for V_{GSO} and V_{DSO} (unbiased condition). Moreover, a very narrow pulse (in the order of 0.1 µsec) is applied. This technique protects the device from being reliant on self-heating due to the applied voltage. As a result, the device's internal temperature is forced to be almost equal to the ambient temperature. The device is then mounted on temperature controlled thermal chuck to heat up the device and therefore the variations in the drain current can be directly linked to the external temperature. The considered device is GaN on SiC substrate with gate width of 2 x 50 µm. It has been characterized at ambient temperature of 25, 40, 55 and 70 ºC.

III. ANN AND SVR MODELING

A. ANN

The well-established, Artificial Neural Networks (ANN) model was inspired by the biological neurons of the human brains. In its basic embodiment, it consists of input layer, hidden layers, neurons or nodes, and output layer. These layers are connected to each other through weights driven connections. Each neuron, takes in the input and multiplies it by its corresponding weights and adds them. Moreover, to scale it above and below a certain threshold value, it adds a bias. The weighted sum is then passed through a transfer function to force its output to a binary range. ANN works as a computing system that attempts to capture the mathematical and intrinsic relationship between the training data. Defining the number of neurons and layers will formulate the model's topology. However, this cannot be set prior to trials. We embarked by creating a one-hidden layer-based architecture and compute the model's performance in terms of mean squared error (MSE) and simulation plots. We noticed that increasing the model's topology will simultaneously affect the model's complexity which in turn upsets the simulation time of the model. So, we carefully changed the model's parameters and repeated the same steps until we got the best topology for this problem. The proposed model's topology consists of three inputs V_{gs}, V_{ds}, and temperature, two hidden layers and an output layer. Each hidden layer consists of four neurons. The proposed architecture utilized to develop the model is shown in Fig.3. Using the model, I_{DS} in terms of V_{DS}, V_{GS} and T can be formulated as follows:

$$I_{DS} = w^3_{bias} + \sum_{i=1}^{4} w_i \tanh(w^2_{i,bias} + \sum_{k=1}^{4} w_{ij} \tanh(w_{1k}V_{GS} + w_{2k}V_{DS} + w_{3k}T + w^1_{bias,k})) \quad (1)$$

where V_{GS}, V_{DS}, and T are extrinsic gate voltage, extrinsic drain voltage and ambient temperature, respectively. w_{1k}, w_{2k}, and w_{3k} are input weights, w_{ij} is the intermediate weights (between two hidden layers), $w^1_{bias,k}$, $w^2_{i,bias}$ and w^3_{bias} are the input-layer, hidden-layer and output-layer biases, respectively. $tanh(.)$ is the non-linear activation function that is used to build the model.

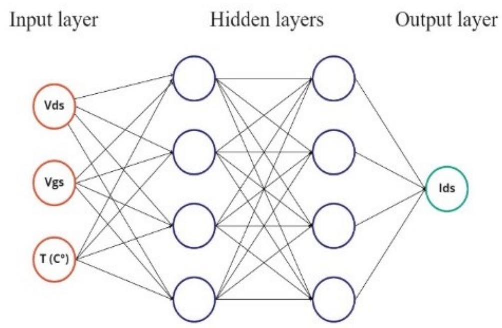

Fig. 3: The proposed ANN architecture

B. SVR

Support vector machine solves pattern recognition problems in which the main objective is to find a hyperplane that differentiates data classes with a certain margin. SVR is the transformation of SVM to solve the regression-based problems. SVR uses kernel functions to transform the data to a higher dimension, additionally it uses some small subsets of the training data called Support Vector (SV) to develop an excellent generalized decision rule [11]. In the SVR modeling, a nonlinear function is used to estimate the fundamental interrelationship between a given input and its respective output [13]. This model can then be used to forecast results for certain inputs not included in the training data.

In principle, the SVR algorithms tries to find out the margin or regression equation, which is maximally deviated by ε from the true values. The entire mathematical framework of SVR in detail can be accesses in [15], [16]. In practice, the predictive function ($f(t)$) for the nonlinear primal function can be described in terms of support vectors.

$$f(t) = \sum_{n=1}^{N} (\alpha_n^* - \alpha_n)\, G(t_n, t) + p \quad (2)$$

where, the terms α_n^* and α_n are the weight coefficients of support vectors, p is the bias and $G(\cdot)$ is the gram matrix. From this we can derive the analytical formula to be implemented in ADS of drain current as follows:

$$I_{DS} = \sum_{n=1}^{N} (\alpha_n^* - \alpha_n) \exp\left(\frac{(t_n - \{[V_{DS}, V_{GS}]\})^T (t_n - \{[V_{DS}, V_{GS}]\})}{2\sigma^2}\right) + p \quad (3)$$

where, t_n, is the support vectors, N is the number of support vectors, σ is the Gaussian kernel parameter and p is the bias. An SVR model is developed with the same training set used for the ANN model. The data is further divided into 10 folds using K-fold cross-validation method with K = 10. Out of 10 folds, 9 folds are used for training and one fold for testing. This process is repeated and average MSE is recorded. The model is developed in MATLAB software environment.

Hyperparameters optimization is the crucial phase to advance the performance of any machine learning model because they directly regulate and control the behaviors of training algorithms and have a huge effect on the accuracy of machine learning models. The proposed work uses the Bayesian optimization technique, which is an iterative approach to optimizing functions without the use of derivatives. In principle there are five hyperparameter: Box Constraint (C), ε- insensitive tube width, kernel Function, Kernel scale and standardization of the data. Bayesian optimization [12], is used to optimize all five parameters owing to its embodiment of probabilistic non-parametric search scheme which is known to outperform some global optimization algorithms [13].

IV. Simulation Results and Discussion

Both ANN and SVR models were developed for the isothermal pulsed IV measurement with zero quiescent bias voltages at four ambient temperatures of 25, 40, 55 and 75 ºC. The gate and drain voltages range between -1 to 7 V in step of 1V and 0 to 30 V in step of 1 V, respectively.

A. ANN

Firstly, the training set is prepared. Due to the different ranges of the features, the features are normalized to be in range of -1 to 1. Normalization is an essential step to enhance the training procedure as without normalization the training functions is harder to converge. The famous multilayer perceptron (MLP) architecture is used with the topology shown in Fig.3. Tan-sigmoid (*tanh(.)*) transfer function is used at input and hidden layer. Pure linear transfer function is used at the output layer. Afterwards, the model is trained using Levenberg-Marquardt backpropagation method. Due to the local optimum dependency of the initial weights and biases the model is trained multiple times until satisfactory results are obtained. The MSE tally is recorded.

B. SVR

The second model is developed using SVR. The model is trained on the same measurement set. The data is pre-processed before feeding to the network. Afterwards, the model is built and optimized. The hyper-parameters are optimized using Bayesian optimizer by running the algorithm for 250 iterations. The optimal values of the hyper-parameters are, Gaussian kernel, standardization of the data, the box constraint equals to 435.76, kernel scale equals to 0.68357 and 0.0015135 for the epsilon. Using these optimal values, the model is trained and later predicted on the validation sets. Moreover, to evaluate the MSE, k-fold cross-validation technique is used and MSE tally is recorded. The average MSE is found to be 2.183e-06.

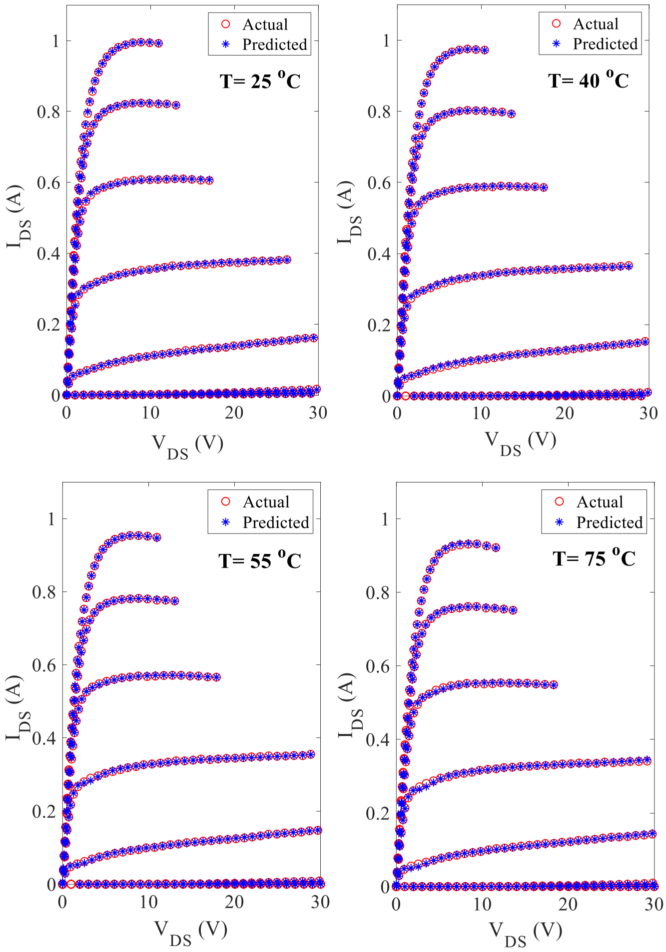

Fig. 4. Predicted IV characteristics of 1-mm GaN HEMT using ANN model.

C. Discussion

To check the robustness of the models, the simulation plots of predicted and measured IV current are shown in Figs. 4. & 5 for the ANN based model and Bayesian optimization augmented SVR based model, respectively. Table 1 reflects the accuracy of the developed models when tested with random set of biases. It can be observed that the SVR model is more robust and produces a more consistent error with the limited data provided compared to that of the ANN due to its embodiment of SRM principle, which drives the training function towards the global minima. The ANN model, however, is easy be implemented in CAD tools. Therefore, a designer can choose either models depending on the requirements.

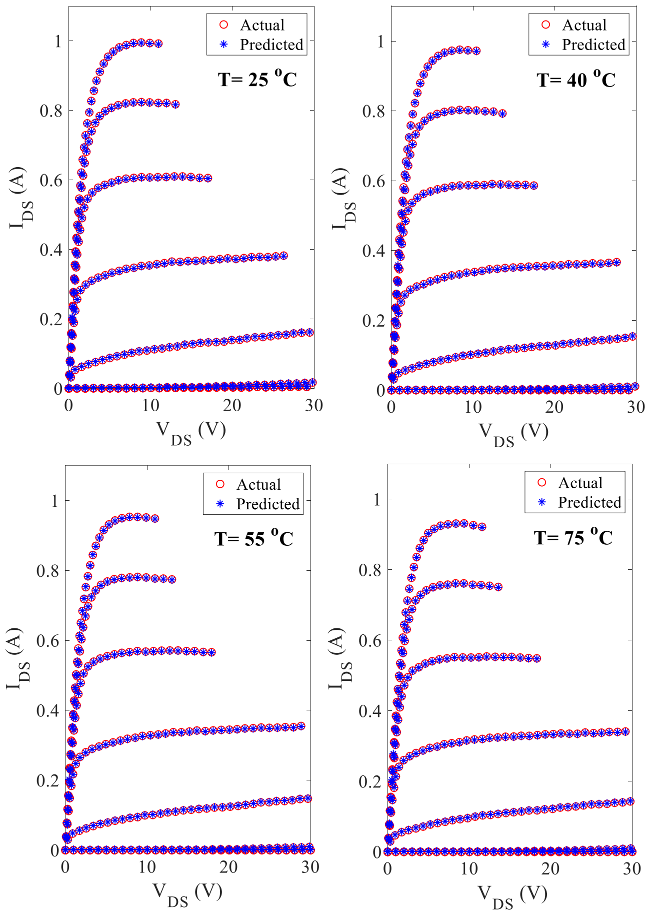

Fig. 5. Predicted IV characteristics of 1-mm GaN HEMT using SVR model.

Table 1: Mean Square Error of five random samples from the data set

Inputs (V_{DS}, V_{GS}, T)	ANN	SVR
06.172 V, 1 V, 25°	1.48E-07	2.03E-06
27.476 V, -3 V, 25°	9.16E-06	2.10E-06
29.063 V, -6 V, 40°	3.33E-08	2.10E-06
02.275 V, 1 V, 55°	5.02E-06	2.30E-06
08.871 V, -3 V, 70°	5.37E-10	2.35E-06
MSE	2.24E-06	2.18E-0.6

V. CONCLUSION

In this paper we have proposed the modeling of the GaN HEMT I-V characteristics including temperature effect as an input using ANN and SVR models. Both models presented excellent results. It is imperative to note that the ANN model has to run multiple times to get the required results. ANN, however, takes less simulation time and memory to store the results and is easy to implantable in ADS software. SVR on the other hand, is more robust and does not need to be trained many times. SVR is also global optimum oriented. However, it takes more time to complete the training, including the optimization time and it requires more memory to store the data. Hence, memory accessing is the main reason why SVR cannot be used for larger datasets.

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