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MODELING OF GaN HEMT BY USING AN IMPROVED K-NEAREST NEIGHBORS ALGORITHM

L. Sang and Y. Xu

EHF Key Laboratory of Fundamental Science
University of Electronic Science and Technology of China
Chengdu 611731, China

Rui Cao

38th Research Institute of China Electronics Technology Group Corporation (CETC38)
Hefei 230088, China

Y. Chen, Y. Guo, and R. Xu

EHF Key Laboratory of Fundamental Science
University of Electronic Science and Technology of China
Chengdu 611731, China

Abstract—A novel black-box modeling method for field effect transistor (FET) based on an improved K-Nearest Neighbors algorithm is proposed in this paper. K-Nearest Neighbors algorithm, which has simple algorithm structure and high accuracy, has shown great potential in regression application. A Taylor series expansion method is employed in nonlinear elements modeling of FET to improve the physical meaning of black-box model. A GaN HEMT power device is used to demonstrate the proposed method. And the experimentation shows that the calculated results using improved K-Nearest Neighbors algorithm based model fit the measurement results well.

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Corresponding author: Lei Sang (sanglei2008@126.com).

1. INTRODUCTION

Recently, AlGaN/GaN HEMT is emerging as a frequently employed technology in high power RF devices due to high maximum cut-off frequency (f_T), high breakdown voltage, high power density and high operating temperature. Accurate nonlinear model is crucial for GaN HEMT devices and circuit designs. Compared with physical based model, the empirical models including equivalent circuit model and look-up table model are simplefast, accurate, and easy to be implemented in commercial software. Therefore, empirical models have been widely used in practical circuits design. As the development of auto measurement system makes data acquisition easier, the look-up table model, which has the best accuracy, becomes an alternative method for device characterization. The artificial neural network (ANN) algorithm has been used as a usual way to establish the look-up table model of FET since ten years ago [9]. However, in spite of many advantages, ANN modeling methods have drawbacks as well. For example, it is difficult to determine proper ANN configurations, and on-convex quadric minimization may result in multiple minima.

As a convenient and accurate algorithm, K-nearest neighbors (KNN) algorithm is simple in structure and easy in implementation. Different from other algorithms as ANN, KNN do not need train and build a function from database which is usually complex. In addition, because the output value is only relevant to partial number of neighbourhood samples, the problem caused by unbalanced number of training samples can be avoided in this algorithm. Due to the advantages above, the KNN algorithm has been used in many fields such as text categorization [1], information processing [2] and earthquake forecast recently [3]. In this study, the KNN algorithm is improved and used to model GaN HEMT device for the first time. A GaN HEMT power device is used to validate the superiority of the algorithm and the proposed method. The Taylor series expansion expressions of intrinsic nonlinear elements are used and described by improved KNN model, which makes the nonlinear characteristic of GaN HEMT represented in numerical way while preserving the original physical meaning of closed-form equation models.

The organization of this paper is as follows. In Section 2, the theory and methodology of KNN is introduced briefly. In Section 3, the improved KNN (IKNN) algorithm is used to build nonlinear model of GaN HEMT device. In Section 4, A GaN HEMT power device is used to validate the method practically. The conclusion of the paper is given in Section 5.

2. THEORY AND METHODOLOGY OF KNN

KNN is a case-based learning method, which uses training data for decision applications. In pattern recognition, a test object denotes a pattern to be predicted, and all candidate patterns are usually described as value labels [4]. Compared with ANN, genetic algorithm (GA) and decision tree (DT) algorithm, KNN algorithm is classified as one of the lazy algorithms, which means that the database would be modeled until a new coordinate value is given [5, 14]. First, the database using KNN algorithm is formed by feature vector with weight in feature space to reduce the complexity as vector space models (VSM). Then the similarity degree between testing data and the databases for every point is calculated. And finally, the most similar K points can be distinguished according to the sum of distance to determine the value of the testing data. The process of KNN algorithm is described as follows

a) Establish a solid database (D) based on the measured results. Set K to be the number of the nearest neighbors. Because K strongly affects the output values yet there is no inherent method for setting. The value is usually determined by experimentation.
b) Calculate and construct M' $(m1, m2 \ldots m_n)$ for each point, where mi is the feature vector. In this study, $m1$, $m2 \ldots m_n$ are the voltages of drain to source (V_{ds}) and gate to source (V_{gs}) respectively.
c) Calculate the distances between M' and each point of the D collection (M): dist (M', M). The Euclidian distance, which is in common use, is adopted with expression

$$d\left(M', M\right) = \sqrt{\sum_{i}^{n} \left(m_i - m_i'\right)^2} \tag{1}$$

d) Choose the K nearest points from D according to the distance calculated above which compose a new data collection (D_k).
e) Calculate the output value of the M' by using the following equation based on $\mathrm{D}_{k.}$

$$M' = \frac{\sum\limits_{i=1}^{K} M_i}{K} \tag{2}$$

3. NONLINEAR FET MODEL BASED ON IMPROVED KNN BASED MODEL

As shown in Fig. 1, a typical equivalent circuit of GaN HEMT device contains parasitic parameters and linear elements extracted from small signal equivalent circuit model (SSECM) and nonlinear equivalent elements calculated based on measurements and numerical algorithm [6].

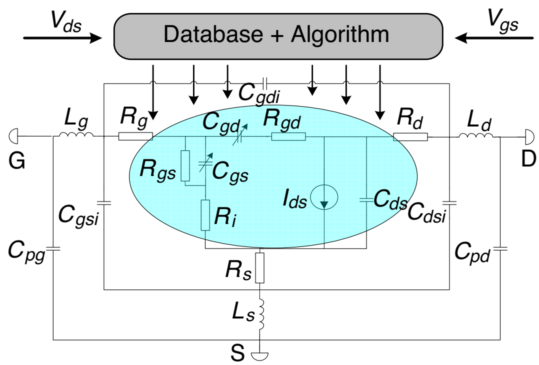


Figure 1. The large signal equivalent circuit for GaN HEMT device.

All the variations of performances versus bias voltages of GaN HEMT device are flat without singular pointswhich is very suitable for the application of KNN algorithm. However, some modifications still need to be added to the original KNN algorithm according to the characteristic of the GaN HEMT device. In short, the improved KNN (IKNN) algorithm has two improvements compared with the original one.

1) Because the disturbing quantity of each characteristic parameter has different changing margins versus the variations of V_{ds} and V_{gs}, the selection of K nearest neighbors needs modify. K is divided into K_d and K_g in this study, where K_d is the number of nearest neighbors to the new point according to V_{ds}, and K_g is the number according to V_{gs}. The larger the disturbing quantity is, the larger the K_d or K_g are. By using the Euclidian distance, the calculation of distance can be described as

$$K = K_d + K_g \tag{3}$$

$$d_d(M', M) = \sqrt{\left(V_{ds} - V'_{ds}\right)^2} \tag{4}$$

$$d_g(M', M) = a \times \sqrt{\left(V_{gs} - V'_{gs}\right)^2} \tag{5}$$

$$a = \frac{\Delta V_{ds}}{\Delta V_{gs}} \tag{6}$$

where V_{ds} and V_{gs} are steps of the two bias voltages, respectively.

2) The output values of the new points are calculated by using the adding weighted formula

$$I = \sum_{i=1}^{K_d+K_g} \frac{(i+K-1)\times(I_i)}{\Psi} \tag{7}$$

$$\Psi = \sum_{i=1}^{K_d+K_g} i \tag{8}$$

where I_i is the value of each point in D_k with arranging order close to the distant.

As shown in Fig. 1, there are three main nonlinear equivalent elements in GaN HEMT device ($I_{ds}(V_{ds}, V_{gs}), C_{gs}(V_{ds}, V_{gs})$ and $C_{gd}(V_{ds}, V_{gs})$), which will be modeled by IKNN for demonstration purpose. The parasitic parameters and linear parameters of GaN HEMT device are extracted by SSECM [8]. The GA algorithm based on Angelov model [7] and ANN algorithm are also used to calculate the nonlinear equivalent elements based on the same database for comparison. The process of modeling HEMT device is shown in Fig. 2.

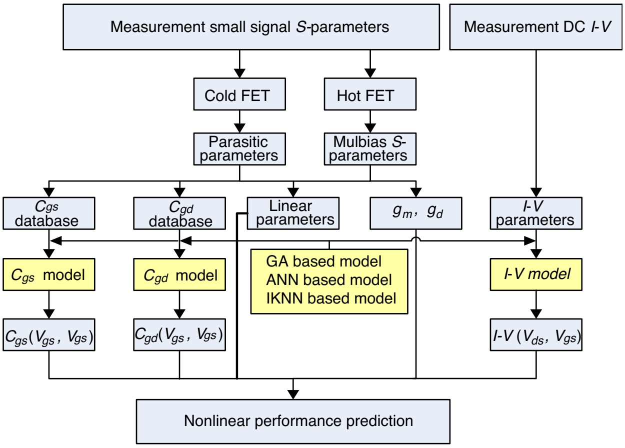


Figure 2. The process chart of modeling.

Typically, the transistor is polarized in a bias point (V_{ds0}, V_{gs0}), and the incremental drain to source and gate to source voltages, V_{ds} and V_{gs}, are applied over this DC polarization. With these premises, it is necessary to accurately reproduce the nonlinear elements $f(V_{ds}, V_{gs}) = F(V_{ds0}, V_{gs0}, V_{ds}, V_{gs})$ dependence and its derivatives with respect to the incremental voltage. In the applications of amplifiers and mixers, the usual method is considering up to the third order inter-modulation distortion (*IMD3*). As a result, the nonlinear elements can be expressed based on Taylor series expansions as follows

$$\begin{aligned} I_{ds}(V_{ds}, V_{gs}) &= I_{ds}(V_{ds0}, V_{gs0}) + G_m V_{gs} + G_d V_{ds} + G_{m2} V_{gs}^2 \\ &\quad + G_{md} V_{gs} V_{ds} + G_{d2} V_{ds}^2 + G_{m3} V_{gs}^3 \\ &\quad + G_{m2d} V_{gs}^2 V_{ds} + G_{md2} V_{gs} V_{ds}^2 + G_{d3} V_{ds}^3 \end{aligned} \tag{9}$$

$$\begin{aligned} C_{gs}(V_{ds}, V_{gd}) &= C_{gs1} + 2C_{gs2} V_{gs} + C_{gsd} V_{gd} + 3C_{gs3} V_{gs}^2 \\ &\quad + 2C_{gsgd} V_{gs} V_{gd} + C_{gsd2} V_{gd}^2 \end{aligned} \tag{10}$$

$$\begin{aligned} C_{gd}(V_{ds}, V_{gd}) &= C_{gd1} + 2C_{gd2} V_{gd} + C_{gds} V_{gs} + 3C_{gd3} V_{gd}^2 \\ &\quad + 2C_{gdgs} V_{gs} V_{gd} + C_{gds2} V_{gd}^2 \end{aligned} \tag{11}$$

where, V_{gd} is the voltage difference between gate and drain electrode. $I_{ds}(V_{ds0}, V_{gs0})$ is the static DC value at bias point, and $G_m, \ldots, G_{d3,} C_{gs1}, \ldots C_{gd3}$ are coefficients related on the Nth order derivatives valuates at the bias point. As a benefit of the great predicting ability of IKNN algorithm, the coefficients of nonlinear elements models can be accurately calculated as the example of G_m and C_{gd3} as below:

$$G_m = \frac{\partial I_{ds}^{IKNN}(V_{ds}, V_{gs})}{\partial V_{gs}} \tag{12}$$

$$C_{gd3} = \frac{1}{3} \frac{\partial^2 C_{gd}^{IKNN}(V_{ds}, V_{gs})}{\partial V_{gd}^2} \tag{13}$$

4. EXPERIMENTAL AND DISCUSSIONS

A GaN HEMT power device was measured and modeled to verify the validation and accuracy of the IKNN based method. The thickness of the silicon carbide (SiC) substrate of the device is 150 μm. The T shape gate is made from Ni/Au with 0.5 μm width. The SiN_x is used as passivation and encapsulation layer. The device consists of a single die (0.56 mm × 1.665 mm chip dimension) with an AuSi eutectic bond to a CMC (Cu/Mo/Cu laminate) ceramic package. The device is encased in ceramic lid attached via an epoxy seal (non-hermetic) forming an open cavity body. The linear elements and parasitic parameters were extracted from small signal scattering parameters by using the

SSECM; the $I_{ds}(V_{ds}, V_{gs})$ database was established directly according to the measurements; the databases of C_{gs} and C_{gd} were established based on the values extracted from measured scattering parameters by means of the SSECM. Matlab code is used as a basis to implement the algorithms, and Fig. 3 to Fig. 4 are the solid databases of the three nonlinear parameters established in the software. The ranges and steps of the databases are shown in Table 1.

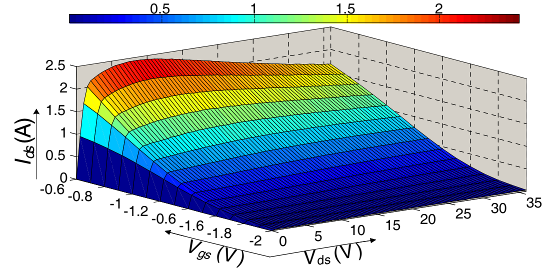
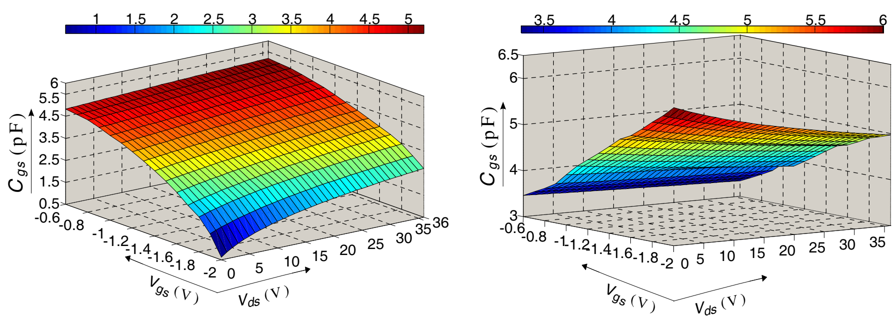


Figure 3. The solid database of I_{ds} established in Matlab.



(a) (b)

Figure 4. The solid databases of (a) C_{gs} and (b) C_{gd} established in Matlab.

Another set of data is used to calculate the accuracy of the three algorithms above (as shown in Table 2). The parameters of the formulas (Eq. (3) to Eq. (6)) are finally set as follows according to the measured data by circular test. In I_{ds} prediction, $K_d = 4$, $K_g = 8$, and $a = 5$. In C_{gs} and C_{gd} predictions, $K_d = 4$, $K_g = 8$, and $a = 10$. The comparisons of the calculated results and measurements are shown in Fig. 5 and Fig. 6.

The Root Mean Square Error ($RMSE$) is used to evaluate the accuracy of the predicted results

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(I_i - I_i')} \qquad (14)$$

where I_i is the predicted value; I_i' is the measured result; and n is the number of test points for validation.

The compared results show that the IKNN algorithm is more accurate than GA algorithm, with simpler structure than ANN

Table 1. The ranges and steps of I_{ds}, C_{gs} and C_{gd} of databases.

Data	databases			
axis	min	max	step	
V_{ds} (V)	0	36	0.5	for I_{ds} database
V_{ds} (V)	0	36	1	for C_{gs} and C_{gd} databases
V_{gs} (V)	-2	-0.6	0.1	for all databases

Table 2. The ranges and steps of the test data for I_{ds}, C_{gs} and C_{gd}.

Data	Test data			
axis	min	max	step	
V_{ds} (V)	0	36	2	for all predictions
V_{gs} (V)	-1.85	-1.25	0.2	for I_{ds} prediction
V_{gs} (V)	-1.65	-1.25	0.2	for C_{gs} and C_{gd} predictions

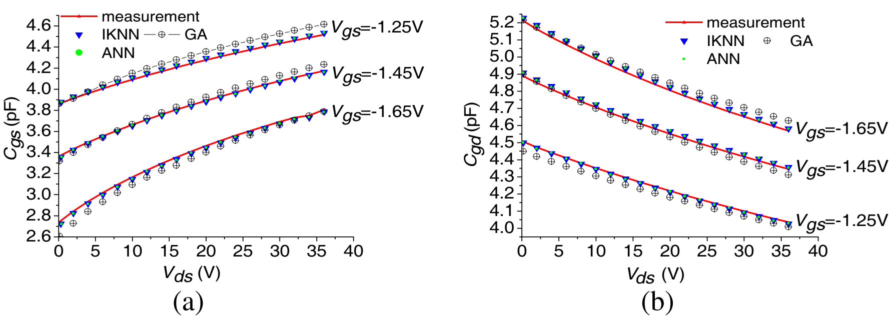
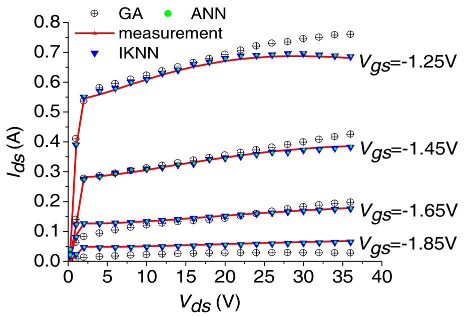
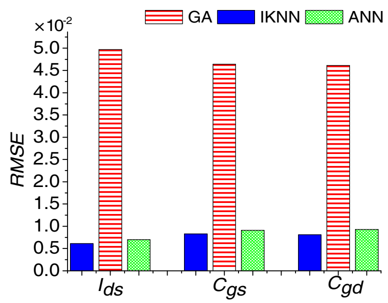


Figure 5. (a) The comparisons of C_{gs} based on IKNN predicted results, GA predicted results, and measured results. (b) The comparisons of C_{gd} based on IKNN predicted results, GA predicted results and measured results.



(a)



(b)

Figure 6. (a) The comparison of I_{ds} based on IKNN predicted results, GA predicted results, and measured results. (b) The comparisons of RMSE between IKNN, GA and ANN models.

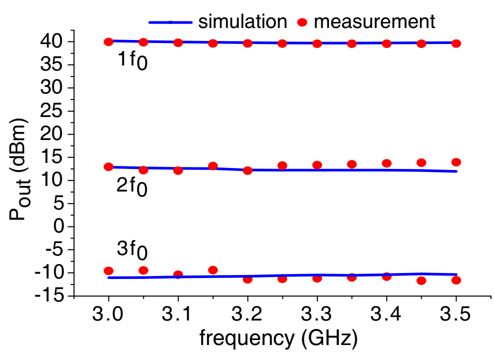
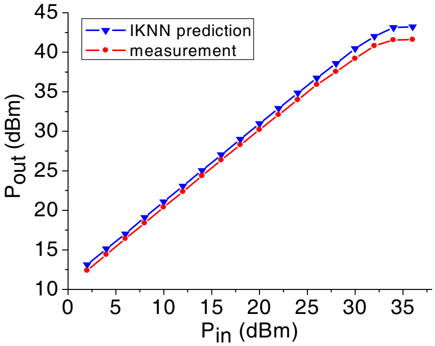


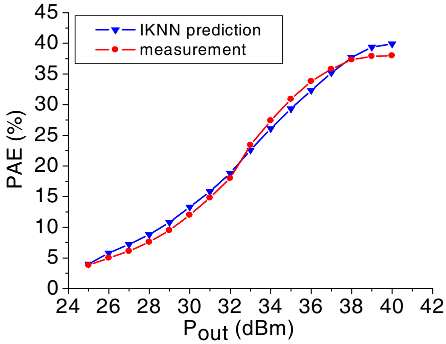
Figure 7. The Output power based on IKNN model and measurements ($P_{in} = 30\,\text{dBm}$).

algorithm. In this study, the IKNN based model is finally used to simulate the nonlinear performances of the GaN HEMT power device. The performances of calculating results based on the IKNN model were compared with measurements in many bias points, and the simulating results fit the testing data well. Take one bias point of them for example. The bias voltages were set as $V_{ds} = 28\,\text{V}$ and $V_{gs} = -1.5\,\text{V}$. The input and output impedances were set to $4.7 - j * 15.3$ and $7.4 - j * 5.8$ respectively with the device leads as measured reference plane [10–13]. Fig. 7 and Fig. 8 are comparisons between simulated and measured results by load pull equipment.

It can be seen that the calculated results based on the IKNN model fit the measured date well. And the results verify that the IKNN algorithm is very suitable for the modeling of GaN HEMT device.



(a)



(b)

Figure 8. (a) the output power versus input power simulated by IKNN based model and measured result ($f = 3\,\mathrm{GHz}$). (b) The power added efficiency (PAE) simulated by IKNN based model and measured result ($f = 3\,\mathrm{GHz}$).

5. CONCLUSION

An improved KNN algorithm is used to build the nonlinear model of GaN HEMT power device in this study. In order to validate the proposed method, a GaN HEMT power amplifier was measured, and three 3-D databases were established based on the measurements. The predicted results calculated by IKNN based nonlinear model, GA based model and ANN based model are compared with the measured results. The results show that the IKNN algorithm is very convenient and suitable to model the nonlinear equivalent elements and can improve the accuracy and applicability of the nonlinear model for the design and analysis of GaN HEMT power device.

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