Optimization of small-signal scalable models of GaN HEMTs using ML techniques

Capstone Report

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Abstract:

The optimization of small-signal scalable models for GaN High Electron Mobility Transistors (HEMTs) is crucial for their efficient application in high-power and high-frequency electronic systems. This project uses Machine Learning (ML) techniques, specifically AdaBoost, Random Forest, and Artificial Neural Network algorithms, to enhance accuracy and reliability of the transistor models. 16 different models will be developed to model the transistor behavior based on the measurement data. Performance metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 scores would demonstrate the models' effectiveness, with high predictive accuracy and strong generalization across varying operational conditions. The results of models highlight the potential of ML overthrowing conventional methods, by overcoming their limitations and providing scalable and robust solutions for optimization of GaN HEMTs. In addition, this work could be foundation for further integration of advanced data-driven techniques in semiconductor device modeling applications.

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Preface

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Chapter 1

Introduction

The demand for an electronic devices that could operate efficiently at high power or high frequencies is rapidly growing alongside with the needs of various industries. These devices are becoming vital part of industrial processes, as they bring a lot of innovative ways for processes optimization and introduces new opportunities. Gallium Nitride (GaN) High Electron Mobility Transistors (HEMTs) have become crucial in the making of such devices, as their superior electrical properties makes them more favorable choice in development of demanded systems. GaN HEMTs also outperform classical counterparts based on Silicon in such properties like breakdown voltage, electron mobility and thermal conductivity. These properties allow the GaN HEMTs to operate in more extreme and unstable conditions. The high temperature or voltages are not causing much degradation for them, which makes them indispensable component in such applications like 5G, 6G, wireless communications, RADAR and LIDAR systems, satellite communication and Power Amplifiers [1, 2]. As the usage of GaN HEMTs in RF/microwave domain, modeling behavior of these devices accurately under small-signal conditions is essential in designing efficient and reliable circuits [3].

The increasing reliance on GaN HEMTs in electronic devices and systems makes it necessary to develop an accurate and scalable small-signal models. These models are fundamental in understanding and predicting of the GaN HEMTs' behavior in varying conditions, as their usage domain is enormous. Particularly, in RF applications the precise signal handling is crucial, as these devices could be used in a critical infrastructure [4, 5]. The developed model should be able to describe the transistor's response to small input signals accurately, as in this domain any minor variations of input could result in unwanted output. These models are vital in designing and optimization of such devices as power amplifiers, oscillators or any other device working at high frequencies [6], so they could work properly. However, traditional modeling techniques have various limitations when it comes to scalability and adaptability of the model. Devices could have different geometries, which causes some challenges in the device modeling process[7].

Small-signal models are mostly constructed using complex physics-based simulations, as in Figure 1.1, or by analysis of experimental data extracted by fitting the equivalent circuits manually [8, 9]. These methods can provide accurate results for a specific parameters of operating conditions, but they struggle with scalability, as when applied to GaN HEMTs with different sizes or fabrication processes. The recent advancements in Machine Learning (ML) sphere are implemented to overcome such challenges and introduced new ways and possibilities for optimizing transistors in various scenarios of usage [10, 11].

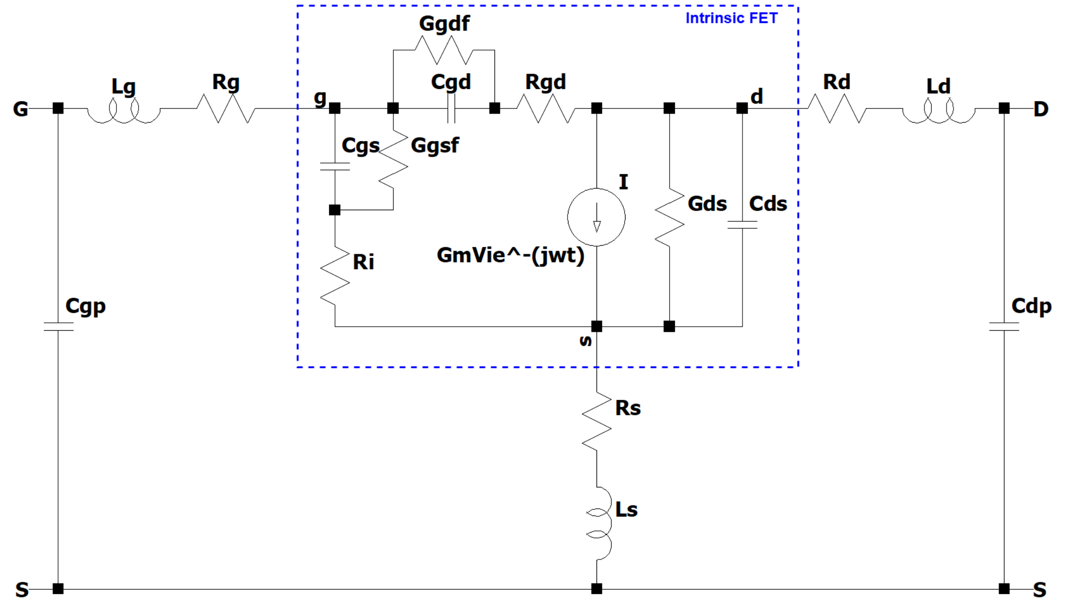

Figure 1.1: GaN HEMT small-signal equivalent circuit model

Machine Learning techniques, especially the regression models, neural networks and support vector machines (SVMs) has been found highly effective in capturing the complex, non-linear relationships, which could often occur in the device's behavior [11, 12]. As it was mentioned traditional modeling methods mostly rely on manual approach in tuning parameters for the desired result, which could miss some interaction patterns in device's behavior. In contrast, ML-driven analysis of large datasets provides the ML-based models capability of generalizing device's performance across different configurations, uncovering some unusual patterns that was overlooked by conventional modeling techniques. This offers a significant advantage of ML-based models over the traditional ones.[13, 14]

Moreover, using ML-driven model allows to automate the process of extraction of the model's key parameters by feeding it only the measurement data. This automation is not only reducing the time and effort required to develop the model, but also minimizes the risk of human error. As GaN HEMTs are increasingly being used in modern devices, the precision and scalability of ML-based models becomes even more valuable. Also, learning more from the provided data allows them dynamically adapt to new designs and conditions. These factors makes the ML-based models offer robust solutions for optimizing the device performance.[15, 16].

In addition, Machine Learning methods have an ability to continuously improve by further training as new data becomes available and provided. Static models developed by traditional methods that needs constant re-calibration for each case. Unlike them, ML-driven models are more flexible and can be retrained easily, allowing them continuous refinement of the model. This provides these models higher accuracy over time. Such adaptive capability is relevant in industries where GaN HEMTs could be deployed for different applications, allowing the model to be used from wireless communications to power management systems.[17, 18] This flexibility is innovative way to retain the model relevant over time, additionally increasing its efficiency and accuracy.

This project aims to use ML-based techniques to optimize the small-signal scalable models with a focus on accuracy, scalability, and generalization of the models across various conditions of device's operation. Integrating ML-based methods should overcome challenges with scalability. Also, this would ensure the accuracy of small-signal models in a broad range of GaN HEMTs avoiding extensive re-calibration of model's parameters [19, 20]. In addition, due automation of the model generation process, ML-based approach would significantly accelerate the design cycle of RF components that use GaN HEMTs, as model only needs time to train itself on the data provided, with small amount of manual work. To achieve these goals, the study will use the Supervised Learning algorithms, such as Random Forest (RF), AdaBoost and Artificial Neural Network (ANN) in creating and training of the models. They will be trained on a datasets of GaN HEMT device measurements, with various range of operating conditions. The ML-optimized models then would be assessed in terms of accuracy, scalability and computational efficiency.

1.1 Ethical and Professional Responsibilities

- **Ethical Responsibility:**
  During the development of small-signal scalable models of GaN HEMTs using ML techniques introduces some ethical concerns that needs to be addressed. One of the primary issues is a risk of bias in data, which is used to train the ML models. If dataset is incomplete or does not represent the diversity of device behavior and operating conditions, the model would lack information to make predictions correctly. The prediction made by model in such case might be inaccurate for some scenarios. As the transistors are used in the critical infrastructure like military, medical apparatus, smart vehicles or devices and in communications, such failure in predictions could result in fatal outcomes. To address this issue, the dataset for training the models needs to be diverse and cover wide range of operating conditions, and data should be pre-processed considering handling of missing values, correct division of data to training and testing sets, and accurate assessment of the developed model's performance. Another ethical issue is the "black box" nature of the ML models. This makes model less transparent and makes it difficult to interpret the decision making process of this model. The lack of transparency could cause accountability issues when used in critical applications, where the understanding of model's algorithm to make decision is crucial. To maximize the transparency of model, the ML-techniques used in the model development would be easy to explain, and more interpretable for humans.

- **Informed Judgments:**
  To ensure that decisions made during this project are well-informed, technical expertise, thorough research and societal implications should be taken into account.

  From the technical perspective, decisions of choosing the machine learning algorithms to develop a model, dataset collection, model validation and performance assessment must be done on empirical evidences and best practices should be used. This includes the understanding of device's physics and properties, exploring the strengths and limitations of ML algorithms that will be used in the project. So that selection of algorithms to develop models would be fair and reasonable, which would be guided by experimentation and testing processes that would be fairly assessed by the correct performance metrics. Such as accuracy of predictions, training speed, computational efficiency and generalization.

  Apart from technical aspects, the societal implications should be considered too. GaN HEMTs are used in broad range of critical industries, like communications, power and control systems, military and healthcare. This makes ensuring the reliability and accuracy of the models not just a technical challenge, but also a societal responsibility, as these devices have direct impact on the society. Additionally, the technology could be misused in harmful purposes. It should be used responsibly with following the ethical guidelines. So, the ethical aspects of the project should be considered alongside with technical ones.

- **Global Context:**
  Optimization of small-signal scalable models of GaN HEMTs using machine learning has a significant global context, as GaN-based technologies has a wide spread of usage in critical spheres like communications, defense, and power systems. GaN HEMTs are capable of operating at high frequencies and maintain their high efficiency. In developed countries the GaN HEMT technology is widely used to enhance energy efficiency, system performance and is a driver for innovative technologies such as 5G, 6G, IoT. However, in developing countries like in regions of Africa or Latin America, access to such technologies could be limited due to economic or social barriers. Ensuring that the benefits of optimized GaN HEMT models are accessible to these regions is important for reducing the digital divide and promoting technological progress. As the ML-based approach is more feasible and much easier to teach than traditional modeling, this would be great opportunity to develop semiconductor sphere in countries with limited resources.

- **Economic Impact:**
  The economic impact of this project can be observed both in short-term and long-term. In the short-term, using ML-based approach in GaN HEMT for the optimization of small-signal scalable models would reduce the time and cost of designing the high-frequency and high-power devices. Automation of the model building process would allow companies to shorten the time spent on each cycle of product development and would make time-to-market faster for new technologies. This would also increase competitiveness between the companies, providing them a strategic advantage in rapid developing technologies. For long-term effects, as the ML-based optimization becomes more popular, the popularity of GaN-based technologies would rise significantly. The low cost and high efficiency of the GaN HEMTs would make it the best choice in electronic devices, which would lead to more efficient designs and accelerate the innovations in semiconductor and electronics sphere. Such a motivation in technology development would also create new market opportunities. On the other hand, such growth and acceleration of the device development cycle could result in much higher demand in GaN HEMT and other semiconductor components. This on other hand would could cause

supply chain pressures and bring problems with material availability and potential increase of the prices on raw materials. Balancing these short and long term impact on the economy is essential for sustainable development of the technologies for electronic devices and wide adaptation of this technology.

- **Environmental Impact:**
In assessment of the environmental impact of the project both perspectives of device modeling and the machine learning should be considered. GaN HEMTs are inherently more energy-efficient than their traditional silicon-based counterparts. This is due to their capability of working at high frequencies and voltages with significantly lower power losses. By optimization of the models for GaN HEMT devices, this project is indirectly contributing to reducing of the energy consumption in industries such as communications, RADAR and LIDAR technologies, and power management systems, in which GaN HEMTs are widely used. Enhanced efficiency in this sectors of infrastructure could lead to less carbon emissions and promote sustainable methods of powering such energy dependent spheres. On the other hand, the increased demand for GaN HEMTs could also harm the environment. Gallium and Nitrogen used in fabrication of these transistors are extracted by methods that pollutes environment and could cause erosion and exhaust the soil and local ecosystems. To minimize these impacts on the environment, energy and material-wise efficient models should be developed, and efforts needs to be done in ensuring responsible extraction of the raw materials for fabrication of the devices. By focusing on the operational efficiency and sustainability, this project would positively impact on the environment.

- **Societal Impact:**
What comes to the societal impact of optimizing small-signal scalable GaN HEMTs using Machine Learning techniques, they are far-stretching, as they are playing crucial role in modern society. GaN HEMTs are integral part of modern communication systems, such as 5G/6G, satellites and IoT. Improvement in performance and scalability of these models would enhance efficiency and reliability of communication systems, resulting in better connection speeds, enhanced mobile and stationary connectivity, and mainly greater access to information for people. Such crucial social spheres as healthcare, where GaN HEMTs are used in medical imaging systems and diagnostic devices, would have positive impact on accuracy of diagnosis and cure for patients and provide more comfortable and reliable apparatus for medical workers. In defense and transportation spheres the accuracy of RADAR and LIDAR technology is vital for safety purposes. However, there could also be such problems as widening of gap between developed and developing

countries could occur. This might happen due to the difference in economical conditions could limit the development of these technologies in developing countries, while the developed ones will have opportunity to invest and rapidly develop this technology resulting in inconsistency of investment to this sphere for the developing countries, as it would be unequal competition with imported products of developed countries. To mitigate this issue, the project aims to focus on easiness of feasibility and accessibility with affordability, ensuring its outcomes could be implemented without problems across diverse regions and industries. This would maximize its societal benefits, contributing to both technological advancements and social equity.

Chapter 2

Background

As it was mentioned before, GaN HEMTs have been a game-changer in the field of high-power and high-frequency electronics. The unique properties of these devices make them a crucial element in applications like radar (Figure 2.1) [21], satellite communications, and 5G/6G network systems. However, as the usage of GaN HEMTs becoming widespread, the need for accurate and scalable models to predict their behavior is growing proportionally. This section will explore the historical context, the limitations of existing modeling methods, and the emergence of ML as an innovative approach in GaN HEMT modeling.

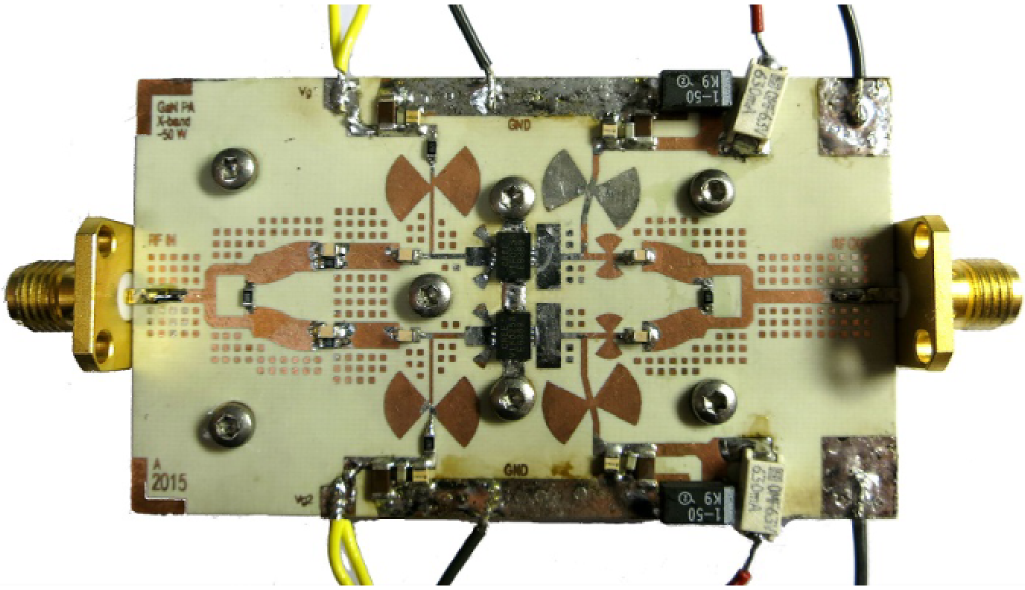

Figure 2.1: GaN HEMT based power amplifier for RADAR system

The development if Gallium Nitride devices offered a new approach in task of creating an efficient and high-performance semiconductor. The Silicon (Si) based semiconductors dominated the industry due to their abundance and well-known behavior. However, the Si-based devices have reached their limits in terms of performance at extreme conditions of operation. While wide-bandgap materials, such as GaN, are more suitable for such usage. The discovery of superior electron mobility and thermal conductivity properties has pushed forward the adaptation of GaN HEMT in industries requiring the devices to operate at extreme conditions.

Accurate modeling of the GaN HEMTs is vital for their usage in electronics' designing. Traditional modeling techniques mostly rely on physics-based or equivalent circuit approaches. This methods have proven their reliability in understanding of device's behavior, but they face a significant challenges when used to model devices with high complexity.

Physics-based models heavily rely on the material's physical properties. This approach is considering developing the model using fundamental equations that describe the electron transport and thermal dynamics. Still, during this modeling process, often the assumptions and simplifications are required to be made, so the computations would be feasible and the model would not require massive amount of computing power. This could affect performance of the model, limiting it in result of accuracy and resource trade-off.

Another approach to model the transistor is equivalent circuit models. The device's behavior is replicated by an electrical network built using lumped elements like resistors, capacitors and inductors. Such models are developed from empirical data, and involve manual fitting of the parameters to match the experimental results. Despite of being more computational efficient and simplicity of this approach, it is highly device-specific and time consuming, as model needs an extensive re-calibration for different configuration even for the same device.

The significant limitations of these approaches are the lack of scalability and difficulties in capturing complex behavior patterns. As the devices' geometries and operation environments could vary, traditional modeling methods would struggle to generalize, demanding interventions for time-consuming manual re-calibrations. Also, usage of predefined equations would limit the model's capability to capture the complex and non-linear behavior of the GaN HEMT across diverse operation scenarios.

Machine Learning has been found as a powerful tool for overcoming the challenges of traditional modeling techniques. Unlike conventional methods that rely on the mathematical formulas that undergoes approximations and simplifications, ML approach uses the analysis of data in large amounts. Such methodology shows its efficiency, uncovering complex and non-linear patterns in device's behavior across various scenarios.

The usage of ML-based approach is not entirely new in the semiconductor modeling. Initial attempts were focused on using regression techniques, to predict transistor device's specific parameters. Only recent achievements in computational power and algorithm development have expanded the capabilities of ML-based approach. Such techniques as support vector machines (SVMs), random forests, and neural networks have emerged as a remarkable tool in modeling complex systems with high accuracy and adaptability.

The main advantage of Machine Learning is the ability to generalize across different configurations. By using extensive datasets for training that include a range of operational circumstances and geometries, ML-driven models can predict the device's performance with minimal manual input and almost fully automated. Such scalability is quite valuable for the fast-paced semiconductor industry, where the cycles of product design are frequent.

So, transition from traditional methods to ML-driven modeling is near future paradigm shift for the whole semiconductor industry. Taking into account the challenges occurring with conventional approach, Machine Learning may offer a reliable framework for modeling transistors' behavior.

Chapter 3

Methodology

3.1 The Dataset and Device Under Test (DUT)

The datasets used for model training was provided by teaching staff of Nazarbayev University. The Device Under Test (DUT) is a GaN HEMT constructed on a 500 μm diamond substrate. The device's general structure can be seen on Figure 3.1. DUT is consists of layers in following order from diamond substrate: 1 nm Aluminum Nitride (AlN) nucleation layer, a 2 μm GaN buffer layer, a GaN channel layer, a 20 nm Aluminum Gallium Nitride (AlGaN) barrier layer, and a 2 nm GaN cap layer. Gate of the device had a geometry of 2 fingers with 125 μm width [22].

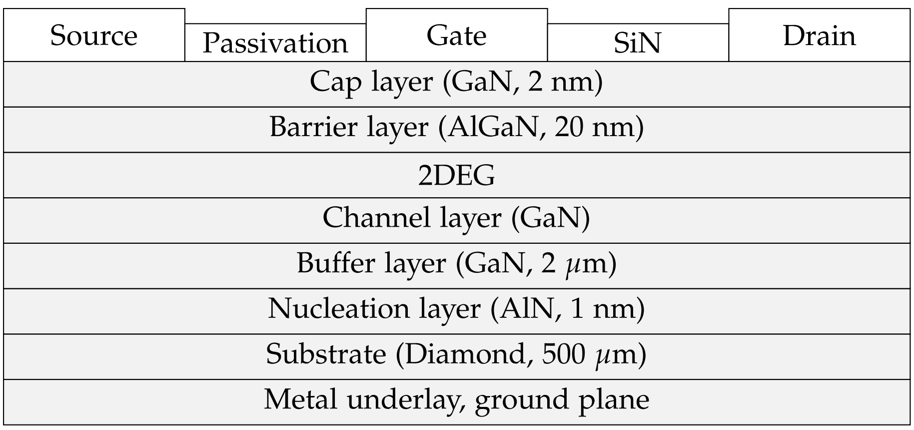

Figure 3.1: DUT structure

Measurements for the dataset were taken using N5245 Vector Network Analyzer (VNA). The data was taken in a range of input configurations, which covers changes in gate-to-source voltage (V_{gs}) from -3 V to 0 V in 0.5 V increments, drain-to-source voltage (V_{gs}) from 0 V to 30 V in 2.5 V increments, frequency (f) from 0.1 GHz to 40 GHz in 0.1 GHz increments and temperature (T) in cases for 25°Cand

85°C. Measured S-parameter (S_{11},S_{21},S_{12},S_{22}) values were taken as magnitude and phase, then converted to complex value.

The final dataset had 12 columns (V_{gs}, V_{gs}, f, T, $S11_{real}$, $S11_{imag}$, $S21_{real}$, $S21_{imag}$, $S12_{real}$, $S12_{imag}$, $S22_{real}$, $S22_{imag}$) and 72800 rows. V_{gs}, V_{gs}, f and T were chosen as input data and S-parameter columns were taken as prediction target separately.

3.2 Data Processing

To develop a good ML-driven model, we should understand the dataset's content. Figure 3.2 shows the distribution for each of the S-Parameter values. It can be clearly seen that the behavior of GaN HEMT device is varying on the different situations. Also, it can be seen that the data has some anomalies in it, such as sudden peaks which are out of the pattern in plot.

After analysis of dataset, various configurations for training and testing sets were analyzed to get the best configuration for training the models. After comparing the performance metrics on default models, it was decided to split dataset by V_{gs} values as criterion. There were 13 unique cases of V_{gs}, and after analysis of default model performances, the training and testing sets were formed from 10 and 3 distinct values of V_{gs} respectively. Testing set was made using V_{gs} values of 20.0, 22.5 and 27.5 V, and leftover values were used to make the training set, making the training and testing data division ratio of approximately 77% and 23% respectively.

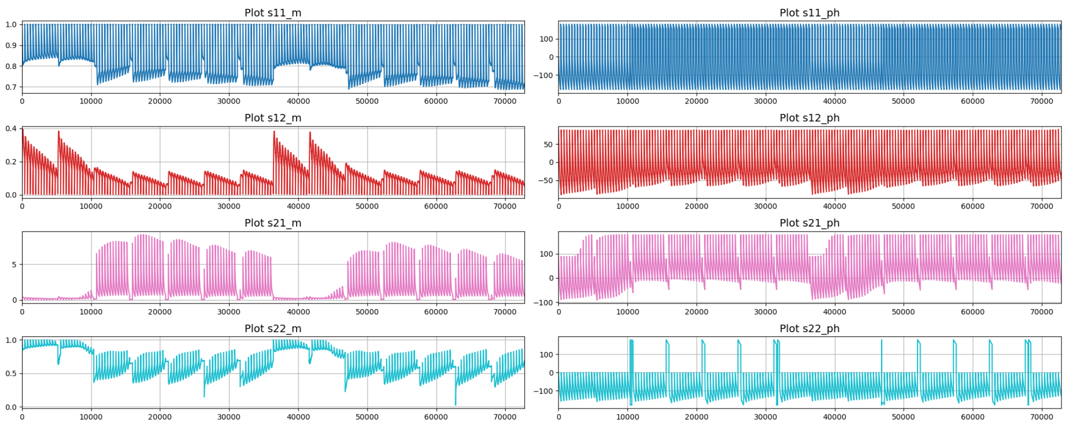

Figure 3.2: Distribution of S-Parameters

Training and testing sets' input data was scaled using MinMaxScaler and normalized to a range of [-1,1] for each of the input variable. Also, the S-parameter values were converted from magnitude and phase degrees to real and imaginary parts, so the output data would be easier to comprehend for the model.

3.3 Model Development

Two distinct types of ML models were developed to predict S-Parameters, AdaBoost with Random Forest (RF) as an estimator and Artificial Neural Network. For each type 8 models were made, so each of the output values would have a separate model, totaling in overall 16 models:

3.3.1 AdaBoost with RF estimator

Adaptive Boosting (AdaBoost) is a boosting algorithm that combines multiple "weak" learners into a stronger one. The main concept of it is to train the "weak" learners sequentially, giving them weights for decision making by focusing on the prediction errors in subsequent iterations. The algorithm is as following:

AdaBoost initializes equal weights for each learner (3.1). Then it starts a cycle, where for each iteration it trains "weak" learners, computes error for each learner (3.2), normalizes them (3.3) and calculates weighted error (3.4). From it algorithm derives a β_t (3.5), which is a weight update factor and uses it to update weights of each learner (3.6) and normalizes them (3.7). In the end, weak learners are combined as a weighted sum of all of them (3.8).

$$w_i^{(1)} = \frac{1}{N}, \quad \forall i = 1, 2, \ldots, N \tag{3.1}$$

$$e_i = |y_i - h_t(x_i)| \tag{3.2}$$

$$E_i = \frac{e_i}{e_{\max}} \tag{3.3}$$

$$\epsilon_t = \sum_{i=1}^{N} w_i^{(t)} \phi(E_i) \tag{3.4}$$

$$\beta_t = \frac{\epsilon_t}{1 - \epsilon_t} \tag{3.5}$$

$$w_i^{(t+1)} = w_i^{(t)} \beta_t^{(1-\phi(E_i))} \tag{3.6}$$

$$w_i^{(t+1)} = \frac{w_i^{(t+1)}}{\sum_{j=1}^{N} w_j^{(t+1)}} \tag{3.7}$$

$$H(x) = \frac{\sum_{t=1}^{T} \alpha_t h_t(x)}{\sum_{t=1}^{T} \alpha_t} \tag{3.8}$$

where:

- $w_i^{(1)}$ - the initial weight assigned to instance i.
- N - the total number of training instances.
- i - indexes the training instances.
- e_i - the absolute error for instance i at iteration t.
- y_i - the actual target value for instance i.
- $h_t(x_i)$ - the prediction of the weak learner at iteration t for instance i.
- t - the current iteration number.
- E_i - the normalized error for instance i.
- $e_{\max} = \max_i e_i$ - the maximum error among all instances.
- $\phi(E_i)$ - the loss function applied to the normalized error E_i.
- ϵ_t - the weighted error of the weak learner at iteration t.
- $w_i^{(t)}$ - the weight of instance i at iteration t.
- β_t - the weight update factor for iteration t.
- $w_i^{(t+1)}$ - the updated weight for instance i for the next iteration $(t+1)$.
- α_t - the coefficient used to weight the weak learner in the final prediction.
- $H(x)$ - the final strong predictor for input x.
- T - the total number of iterations (weak learners).
- $h_t(x)$ - the prediction of the weak learner at iteration t for input x.

For the role of "weak" learner in AdaBoost the Random Forest was chosen. RF is an ensemble method, that builds multiple decision trees and combines them by finding their average. So, every tree in the forest has equal weight in the final model. Mathematical basis of RF can be shown as following:

$$H(x) = \frac{1}{T} \sum_{t=1}^{T} h_t(x) \tag{3.9}$$

where:

- $H(x)$ - the final predictor
- T - the total number of trees.

- $h_t(x)$ - tree predictor

Hyper-parameters for the AdaBoost with RF estimator were tuned using the Random Search method. The parameter grid was provided with following hyper-parameters and values for them were arranged based on the default value for each of the parameter.

For RF estimator:

- n_estimators - The number of trees in the forest
- max_depth - The maximum depth of each tree
- min_samples_split - The minimum number of samples required to split an internal node
- min_samples_leaf - The minimum number of samples required to be at a leaf node
- max_features - The maximum number of features to consider when looking for the best split
- max_leaf_nodes - The maximum number of leaf nodes in the tree

For AdaBoost:

- n_estimators - The number iterations
- learning_rate - The learning rate of the model

3.3.2 Artificial Neural Network

Artificial Neural Network (ANN) - a computations model which takes inspiration from the human brain's neural network. Model is made from interconnection of artificial neurons built in layers. They process information using the connectionist approach. Structure of ANN is generally Input layer, 1 or multiple Hidden layers and an Output layer (Figure 3.3).

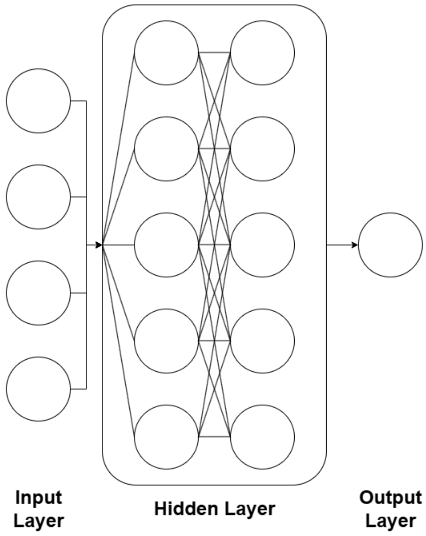

Figure 3.3: Approximate schematic of ANN structure

To tune ANN models the manual approach was used. The process began with a complex architecture of ANN that was gradually simplified until the model achieved reliable performance without signs of overfitting. The resultant models had a structure 4-20-20-20-1 (neuron number per layers) for all cases.

3.3.3 Evaluation Metrics

To assess the model's performance following metrics were used:

- Mean Squared Error (MSE):

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3.10}$$

  where y_i is the actual value, $\hat{y}_i$ is the predicted value, and n is the number of data points.

- Mean Absolute Error (MAE)

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{3.11}$$

  where y_i, $\hat{y}_i$, and n are as defined above.

- R^2 Score

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3.12}$$

  where $\bar{y}$ is the mean of the actual values y_i and y_i, $\hat{y}_i$, and n are as defined above..

Chapter 4

Results and Discussions

This section presents the performance evaluation of the machine learning models developed using AdaBoost and ANN algorithms. The models were designed to predict values for real and imaginary parts of complex S-Parameters for the specific device. To assess the performance such metrics as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 score will be analyzed.

4.1 AdaBoost with RF estimator

				Training:				
	S11 Real	**Imag.**	**S21 Real**	**Imag.**	**S12 Real**	**Imag.**	**S22 Real**	**Imag.**
MAE	8.37E-03	5.35E-03	2.57E-02	4.74E-02	2.00E-03	2.66E-03	3.98E-03	4.06E-03
MSE	1.08E-04	4.09E-05	1.06E-03	3.43E-03	5.57E-06	1.05E-05	2.24E-05	2.20E-05
R^2	0.9995	0.9997	0.9995	0.9979	0.9986	0.9981	0.9999	0.9996
				Testing:				
	S11 Real	**Imag.**	**S21 Real**	**Imag.**	**S12 Real**	**Imag.**	**S22 Real**	**Imag.**
MAE	9.17E-03	6.87E-03	3.27E-02	5.29E-02	5.98E-03	5.94E-03	2.66E-02	2.11E-02
MSE	1.44E-04	7.55E-05	2.59E-03	4.55E-03	5.89E-05	5.24E-05	8.96E-04	5.93E-04
R^2	0.9993	0.9994	0.9991	0.9975	0.9675	0.9801	0.9945	0.9779

Table 4.1: Performance results of AdaBoost models

The Table 4.1 is a summarized representation of all AdaBoost based models' performance. Each model was evaluated using training and testing data to assess their generalization and accuracy capabilities.

4.1.1 Model Performance Overview (AdaBoost)

Training Performance

The training results reflect the ability of models to learn from the provided data. MAE and MSE values reveal us the error rate in predictions while training the model. The $S_{12_{real}}$ model exhibited the lowest training errors, with an MAE of 2.00×10^{-3} and an MSE of 5.57×10^{-6}, demonstrating excellent accuracy in capturing the device's small-signal behavior. But some models such as for $S_{21_{imag}}$, showed slightly higher training errors with an MAE of 2.57×10^{-2}, and relatively high MSE of 1.06×10^{-3}, reflecting the inherent complexity in modeling imaginary part behavior. As for the R^2 values, they were consistently high across all models, with the lowest score being 99.79% ($S_{21_{imag}}$) and all of them exceeding 99%. These results indicate that the models effectively explain the variance in the training data, which is a strong indicator of their reliability.

Testing Performance

The testing results demonstrate the models' generalization capabilities when exposed to unseen data. For MAE and MSE values at testing the values have not altered much, model for $S_{11_{imag}}$ achieved a test MAE of 6.87×10^{-3} and a test MSE of 7.55×10^{-6}, revealing the models' capability to predict even on the unseen data. Similarly The test R^2 scores remained high, with $S_{11_{imag}}$ achieving 99.94% and $S_{11_{real}}$ scoring 99.93%. These scores confirm that the models generalize well and maintain high predictive accuracy across diverse operational conditions. However, on models for S_{21} and $S_{22_{imag}}$ we can see that test R^2 is lower than in training, and falls to 96.75%, 98.01% and 97.79% respectively. This is noticeably lower than its training counterpart, which indicates that model is most likely overfitted and needs to be tuned better. But after many trials of tuning the model, these are considered as best results. Still models do a great job in predicting device's behavior on unseen conditions' data.

The results show that there are very small deviations across metrics of training and testing. The real models showed a very good performance, as these values tend to have linear relationships, which are easy for ML model to capture. On the other side evaluation of imaginary models also resulted in good predictions but their error values were higher in comparison to real models. This due to the non-linear nature of the imaginary part of complex S-parameter values, which are harder to capture, but still AdaBoost model could effectively do it. Overall, AdaBoost model demonstrated its consistency and robustness in S-Parameter predicting and good results even on unseen data demonstrates its great ability to generalize effectively, which highlights AdaBoost's practical applicability.

4.2 ANN

Training:								
	S11 Real	**Imag.**	**S21 Real**	**Imag.**	**S12 Real**	**Imag.**	**S22 Real**	**Imag.**
MAE	5.90E-03	3.89E-03	1.60E-02	1.14E-02	1.04E-03	1.93E-03	5.54E-03	3.95E-03
MSE	5.31E-05	2.81E-05	5.18E-04	2.57E-04	1.85E-06	5.84E-06	5.03E-05	2.59E-05
R^2	0.9998	0.9998	0.9998	0.9998	0.9995	0.9989	0.9997	0.9996
Testing:								
	S11 Real	**Imag.**	**S21 Real**	**Imag.**	**S12 Real**	**Imag.**	**S22 Real**	**Imag.**
MAE	6.34E-03	4.15E-03	1.62E-02	1.23E-02	1.12E-03	2.20E-03	7.16E-03	4.33E-03
MSE	5.43E-05	3.00E-05	5.05E-04	3.26E-04	2.21E-06	7.25E-06	7.25E-05	3.10E-05
R^2	0.9998	0.9998	0.9998	0.9998	0.9988	0.9972	0.9996	0.9988

Table 4.2: Performance Metrics of ANN for S-Parameters

The performance of the ANN models is summarized and shown on Table 4.2. Each model's metrics, evaluated on both training and testing datasets, reveal its predictive power and generalization ability.

4.2.1 Model Performance Overview (ANN)

Training Performance

As it was mentioned above, MAE and MSE values reveal us the error rate in predictions while training the model. For ANN too, the model for $S_{12_{real}}$ achieved the lowest training error among other models with an MSE of 1.85×10^{-6} and MAE of 1.04×10^{-3}. Imaginary part models generally showed higher MSE and MAE values. For example, $S_{21_{imag}}$ recorded an MSE of 2.57×10^{-4} and MAE of 1.14×10^{-2}. This relative high value for error happens due to mentioned non-linear behavior of imaginary values, which is more challenging to capture accurately. As for R^2 values, all models exhibited exceptionally high R^2 score during training, with some of them achieving almost perfect 99.98%.

Testing Performance

What comes to testing data results, MSE and MAE there where slightly higher but almost same to the training values. The pattern of error values for models resembled same also in testing cases. Just as in AdaBoost case models for S_{21} and $S_{22_{imag}}$ showed worse results, but drop is not drastic as in AdaBoost and is in range of approximately 0.1%. The low error values and high R^2 score values, like close to perfect 99.98% demonstrates a great performance even on unknown data.

The ANN models showed excellent performance in predicting S-Parameters both for real and imaginary values. The models demonstrated high accuracy and exceptional ability to generalize across unseen data. Such results highlights the potential of ANN usage in transistor behavior prediction, and validates the effectiveness of neural networks in addressing the challenges of semiconductor device modeling.

4.3 Comparative Analysis

Tables 4.3 and 4.4 demonstrates the time consumed for models to be ready-to-use and their hyper-parameters. Table 4.5 summarizes the main measures of the AdaBoost and ANN models for comparison purposes.

Time (seconds):								
	S11 Real	**Imag.**	**S21 Real**	**Imag.**	**S12 Real**	**Imag.**	**S22 Real**	**Imag.**
Tuning	2933.41	2258.62	2779.83	2228.21	2242.33	3359.22	2167.87	2327.81
Training	24.4	38.1	33.5	15.9	25.1	21.0	10.6	64.2
Prediction	11	15.6	13.7	6.5	8.0	8.4	2.5	29.7
Hyper-Parameters:								
	S11 Real	**Imag.**	**S21 Real**	**Imag.**	**S12 Real**	**Imag.**	**S22 Real**	**Imag.**
n_estimators	80	80	70	30	90	50	30	90
min_samples_split	10	10	10	10	2	2	10	2
min_samples_leaf	1	2	2	1	2	2	2	2
max_depth	9	11	11	5	9	8	12	9
ada_estimators	80	80	70	70	80	50	70	90

Table 4.3: AdaBoost Timing and Hyper-Parameters

Time (seconds):								
	S11 Real	**Imag.**	**S21 Real**	**Imag.**	**S12 Real**	**Imag.**	**S22 Real**	**Imag.**
Training	204	193.6	203.7	199.4	201.1	200.9	198.2	218.3
Prediction	3.2	3.1	3.2	2.9	3.3	3.2	3.1	3.4
Hyper-Parameters:								
	S11 Real	**Imag.**	**S21 Real**	**Imag.**	**S12 Real**	**Imag.**	**S22 Real**	**Imag.**
Epoch	200	200	200	200	200	200	200	200
Batch Size	32	32	32	32	32	32	32	32
Model Structure	4-20-20-20-1							

Table 4.4: ANN Model Timing and Hyper-Parameters

Model	Avg. Time (s)	Avg. MSE	Avg. R^2 Score	Avg. MAE
AdaBoost	2578.19	1.12E-03	98.94%	2.02E-02
ANN	205.58	1.28E-04	99.92%	6.73E-03

Table 4.5: Summary Comparison of AdaBoost and ANN Models

As we can see, in terms of prediction accuracy, the ANN models outperformed AdaBoost ones. They got noticeably lower values of MSE and MAE, resembling high R^2 score and demonstrated a much lower time consumption. This can also be noted on Figures 4.1, 4.2, 4.3 below:

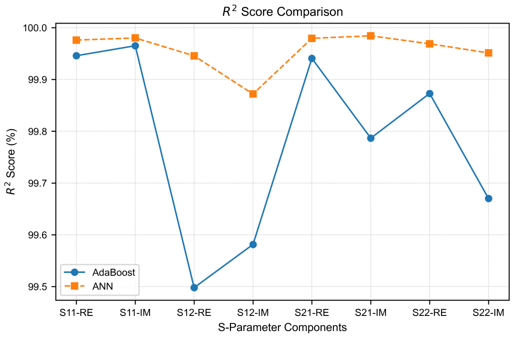

Figure 4.1: R^2 Score Comparison of AdaBoost and ANN Models

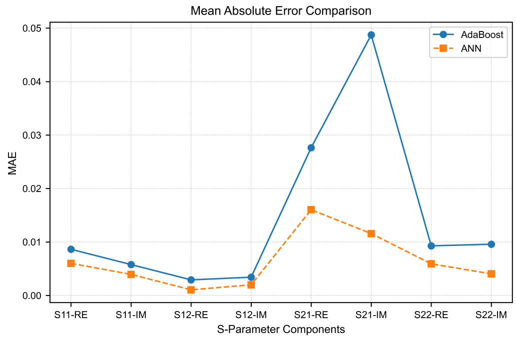

Figure 4.2: Mean Absolute Error (MAE) Comparison of AdaBoost and ANN Models

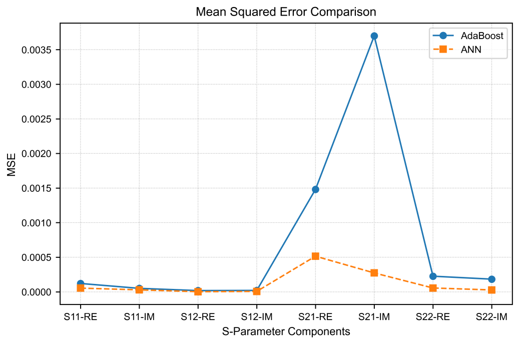

Figure 4.3: Mean Squared Error (MSE) Comparison of AdaBoost and ANN Models

Smith Charts were plotted for S-parameters at various bias points; it can be seen in Figures 4.4-4.11 below. We can see that in some bias points S_{21} predictions are not following the measured values, which indicates some inaccuracies in the model predictions. But overall, the pattern is still preserved, and behavior of the device is resembled.

The Figure 4.12 has a 3D plot of MSE values for bias points in testing set. From the graphs we can see that ANN models demonstrated much better results in terms of error compared to AdaBoost.

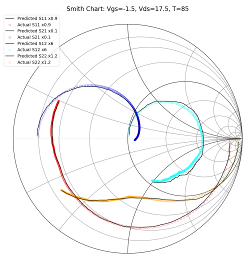

Figure 4.4: Smith Chart for AdaBoost at V_{gs}=-1.5, V_{ds}=17.5, T=85

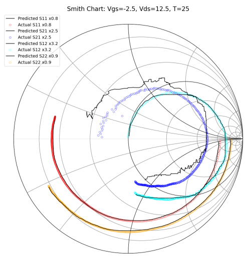

Figure 4.5: Smith Chart for AdaBoost at V_{gs}=-2.5, V_{ds}=12.5, T=25

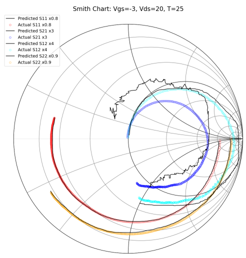

Figure 4.6: Smith Chart for AdaBoost at V_{gs}=-3.0, V_{ds}=20.0, T=25

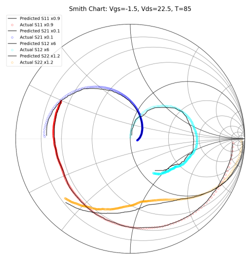

Figure 4.7: Smith Chart for AdaBoost at V_{gs}=-1.5, V_{ds}=22.5, T=85

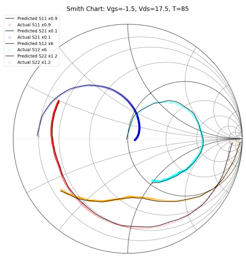

Figure 4.8: Smith Chart for ANN at V_{gs}=-1.5, V_{ds}=17.5, T=85

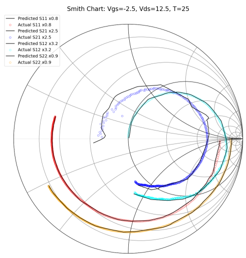

Figure 4.9: Smith Chart for ANN at V_{gs}=-2.5, V_{ds}=12.5, T=25

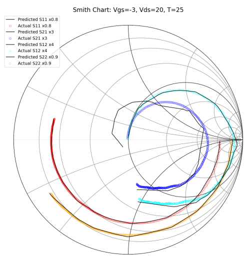

Figure 4.10: Smith Chart for ANN at V_{gs}=-3.0, V_{ds}=20.0, T=25

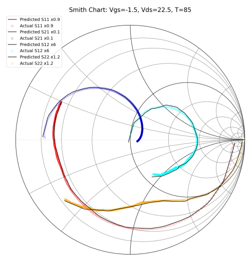

Figure 4.11: Smith Chart for ANN at V_{gs}=-1.5, V_{ds}=22.5, T=85

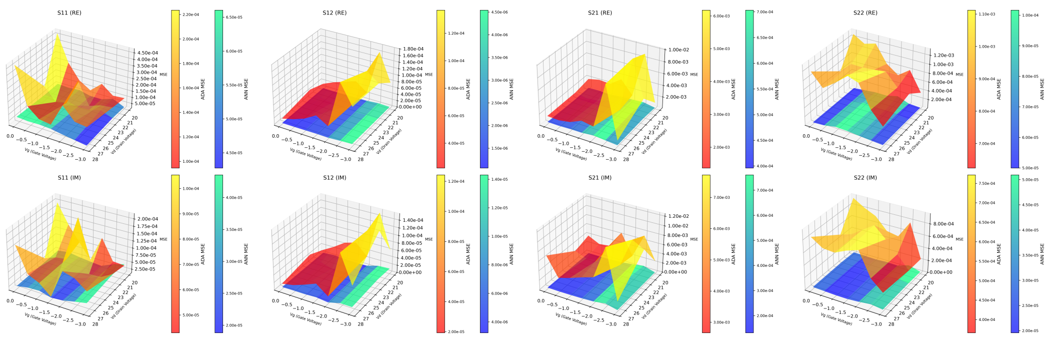

Figure 4.12: MSE by Bias Points

Chapter 5

Conclusion

In conclusion, this project demonstrated the potential of machine learning techniques, particularly AdaBoost and ANN, in applications like optimization of small-signal models for GaN HEMTs. Both of the algorithms showed exceptional accuracy of predictions and generalization capabilities in terms of different operation environment. The models resulted in low error rates and high R^2 scores, which indicates their reliability for real-world applications.

The usage of ML aids in overcoming challenges of traditional modeling, such as scalability and adaptability. The automation of parameter extraction and reducing the need of manual re-calibrations, these models offer much efficient and faster approach for modeling the complex devices like GaN HEMTs. In addition, the ML-driven models are adaptive, which allows them to improve over time, ensuring their long-term relevance.

Future works could focus on expanding the research domain by covering more conditions with larger datasets, or by implementations of other types of neural networks and architectures to enhance the performance of ML-based models. Also, these type of behavioral models could be tested to be used in CAD programs, to ensure their usability in device development and simulation. Integration of such algorithms in industry would positively affect the designing process, by accelerating the design cycle and reinforcing GaN HEMTs' position as the driver of innovation in electronics domain.

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