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A Systematic Review of Machine Learning-based Small-Signal Modeling Approaches for Gallium Nitride High Electron Mobility Transistors: Performance Analysis and Algorithmic Insights

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Machine learning (ML)- based modeling is an evolving and thriving research field that must be kept up to date with technological advancements. This paper presents an in-depth analysis of Gallium Nitride High electron mobility transistor (GaN HEMT) behavioral modeling using ML techniques. Through a comparative analysis of ML-based approaches, we explore the development of HEMT models, encompassing scattering parameters, C-V and I-V characteristics, thermal profiles, and more. It also explores conventional techniques and their limitations, emphasizing the advantages of ML applications. This study systematically identifies, analyzes, summarizes, and reports the current state of utilization of ML in the modeling of GaN HEMT. The study critically assesses various ML techniques, including regression, optimization, Artificial Neural Network (ANN), Support Vector Regression (SVR), Decision Tree (DT), Particle Swarm Optimization (PSO), and genetic algorithms (GA), etc. considering precision, complexity, and computational efficiency. Intended for engineers and researchers in electronic and semiconductor devices, this paper serves as a crucial resource, fostering cross-disciplinary collaboration and aiding in the selection of appropriate modeling algorithms in this rapidly progressing field, thereby contributing significantly to the existing literature.

Keywords: GaN; HEMT; Machine learning; Small signal modeling; ANN; Semiconductor

1 Introduction

The High Electron Mobility Transistor (HEMT) is a type of field-effect transistor that employs a hetero junction as the electron flow channel. A heterojunction is created when two materials with different band gaps come into contact with one another[1]. Traditional MOSFETs and MESFETs require short channel lengths in order to attain applications in high-frequencies $F_T = v_{sat}/2\pi L^2$. Additional requirements for high frequency are low noise levels and high power densities, but these limitations in terms of high saturation current and large transconductance are attainable through heavy doping. However, heavy doping in the channel leads to scattering, which reduces the mobility of electrons and, hence, the saturation velocity. To overcome the effect of scattering due to doping, heterojunction is used to increase mobility.

Therefore, HEMTs meet all requirements of High application[3,4]. The emergence of gallium nitride high-electron-mobility transistor (GaN HEMT) devices[5,6] has the potential to deliver high power and high frequency with performances surpassing mainstream silicon and other advanced semiconductor field-effect transistor (FET) technologies which are surveyed by Haziq *et al*.[7]. As shown in Fig. 1(a), GaN HEMTs have a similar structure to GaAs HEMT but perform better than it due to their outstanding properties as shown in Table 1. It is widely known that HEMT devices made with AlGaN/GaN are superior to those made with other materials[11].

Modeling is the process of creating simplified representations of complex systems to predict and analyze their behavior under various conditions. It involves mathematical, physical, or computational techniques to capture the essential characteristics of a system. In the context of electronic devices, modeling enables accurate simulation and optimization, improving the design and performance of these systems.

Accurate models are crucial to provide valuable feedback to technologists and circuit designers to advance and develop GaN technology continuously[13,14]. Many studies, as briefly discussed in Section 2, have been conducted on the linear and nonlinear high-frequency modeling of GaN HEMTs,

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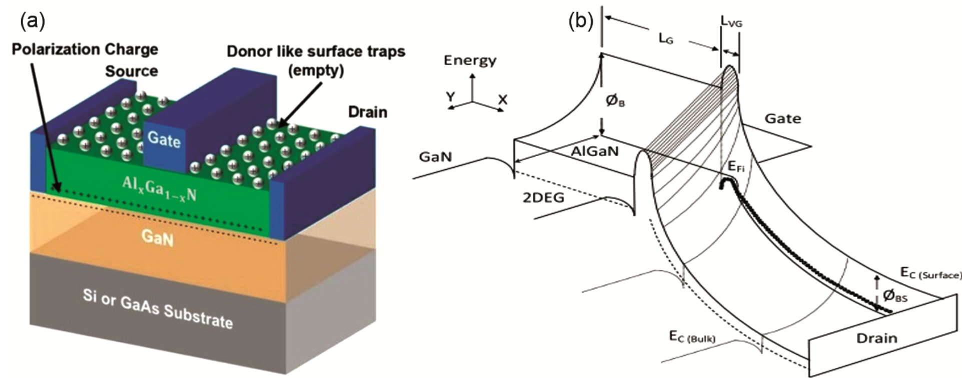

Fig 1 — GaN HEMT structure and band diagram

Table 1 — Comparison of GaN with different Semiconductor materials[8-10]

Properties	GaN	Si	GaAs	SiC	InP
Electron Mobility (cm2/Vs)	2000	1300	5000	260	5400
Bandgap Energy Eg(eV)	3.39	1.1	1.4	2.9	1.35
Electric Breakdown Field Ec (kV/cm)	3300	300	400	2500	500
Dielectric Constant	9.5	11.4	13.1	9.7	12.5
Saturated Electron Drift Velocity ($X10^7 cm/s$)	2.5	1.0	1.0	2	1.0
Thermal Conductivity x (W/cmK)	1.3	1.5	0.46	4.9	0.7

with a primary focus on obtaining the small-signal model[15-24]. Accurately modeling GaN HEMTs is challenging due to their complex small-signal behavior and the intricate interplay of physical parameters, which conventional approaches struggle to capture. Machine Learning techniques, known for their exceptional learning and generalization abilities, offer a powerful alternative, allowing for direct simulation of S-parameter measurements without needing equivalent circuit representations. In an age of rapid technological advancement, these cutting-edge methods make device behavior prediction, precise optimization, and reliable and efficient development of HEMTs easier[25-32]. For the superior performance researches are exploring deep learning approaches as well[33-35], Using extensions of ANNs that have gained popularity in recent years due to their superior performance, such as standard recurrent neural networks (RNNs) and their advanced variants like long-short term memories (LSTM) and gated recurrent units (GRU), is another valuable behavioral approach[36-39] and large signal behavioral modelling of GaN HEMT using Description and application of ML approaches applied to small signal are also being explored continuously and rapidly[40-42].

This paper enhances the understanding of the intricate relationship between GaN HEMTs, small-signal behavioral modeling, and ML techniques. It reviews current research on GaN HEMT modeling and ML integration, offering insights for selecting effective modeling algorithms. The study aims to serve as a semiconductor device modeling resource and promote cross-disciplinary collaboration in this rapidly evolving field. In the current study, noteworthy papers published till 2024 known to the author after removing the similar/duplicate work are reported. This current review aims to summarize, analyze, and comprehend the studies are based on the following aspects:

- Papers with small signal modelling of GaN HEMT using ML application are identified.
- Various Algorithms and architecture used in behavioral modelling are analyzed and studied.
- Details of work done (I-V, C-V, S-parameter, etc.)
- Identification of various error metrics used in each paper.
- Comparison of various techniques and work in a tabulated form.

To achieve this purpose, several digital libraries were exhaustively investigated, and relevant studies were identified and incorporated into this review in order to address the Research Questions (RQs) discussed later in this article. This is how the rest of the article is organized: Section 2 talks about the overview of conventional small-signal modeling techniques and the pros and cons of the same used to create the basis of the study to learn the importance of ML-based small-signal modeling. Section 3 discusses the basics

of Machine learning and the application of ML in GaN HEMT modeling. Section 4 talks about the Review methodology encompassing RQs and paper selection criteria. Section 5 is the literature review which is the heart of the paper. Section 6 discusses how performance evaluation is done in the literature to understand the results. Section 7 discusses the challenges and issues with ML-based modeling, and section 8 has a conclusion followed by a future direction.

2 Overview of Conventional Small-Signal Modeling Techniques

RF and microwave circuit design requires modeling to predict frequency response, gain, stability, and noise for performance analysis. It also extracts transconductance, output conductance, and capacitances, which are essential for understanding device behavior under different operating conditions. Small-signal models simplify circuit simulation and optimization, optimizing bandwidth, gain, and efficiency. For applications that require precise control and stability, such as communication systems and radar technologies, accurate small-signal models are needed to predict HEMT linear behavior across a wide frequency range[1].

There are various approaches to HEMT modeling, each with its own advantages and limitations. Fig. 2 represents the Fundamental modeling approaches which are briefly explained in this section:

2.1 Physics Based Modelling

Physics-based compact models are created by solving the fundamental physical equations governing charge formation and transport. Charge formation is governed by Poisson's and Schrodinger's equations, while charge transport is effectively described by the device's drift-diffusion model, which includes material properties, device geometry, and electrostatics. These models express physical quantities of interest as analytical functions of input variables, such as voltage, temperature, and geometry. Advanced Spice Model for GaN HEMTs, ASM-HEMT, which is a physics-based compact model derived from the core formulations of the surface potential. These models offer deep insights into device operation and provide valuable information about the factors influencing performance. However, a significant drawback of physics-based models is their complexity; the intricate behavior of advanced semiconductor devices results in complex mathematical formulations, increasing simulation time and reducing efficiency. To mitigate this, engineering approximations are often made to simplify the model and maintain practical simulation times. The main advantage of these models lies in their accuracy and ability to predict device behavior under various conditions. Still, their complexity can be a limitation in terms of computational resources and time[43,44]. The physical models may further be categorized into Threshold voltage-based, Surface potential-based, and charge-based. A lot of prominent research work has been done in this area[45-47,43].

2.2 Behavioral Model

In contrast to a physical model, which is a mathematical description of the underlying physical mechanisms governing the operation of a particular device, a behavioral model focuses solely on the device's observable input-output relationships.

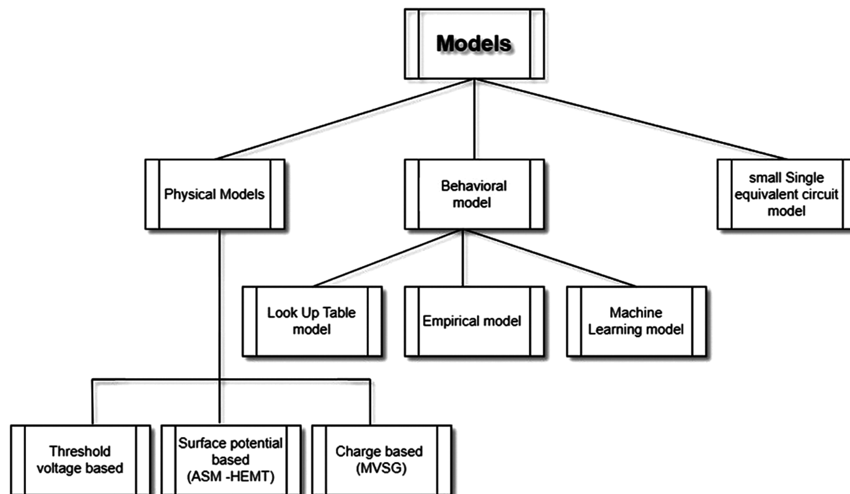

Fig 2 — Fundamental modelling approaches

A behavioral model depicts the behavior of a device without getting into the intricate details of its operation. This can be accomplished by utilizing various mathematical techniques, such as ML to develop a black box model, rational frequency functions, approximating polynomials, or interpolated lookup tables (LUTs) to determine the ratio between output and input voltage phasors.

2.2.1 Lookup Table

A look-up table model simplifies this process by using precomputed data to approximate the device's behavior. This involves measuring the HEMT's characteristics under various operating conditions and storing the results in a table. The table contains a set of input-output pairs, where the input is the operating condition (such as gate voltage or drain current), and the output is the corresponding HEMT response (such as drain current or transconductance). During simulation, the look-up table model retrieves the appropriate input-output pair from the table and uses it to approximate the device's behavior. The model's accuracy depends on the density and range of the data points in the table. Overall, the look-up table model is a beneficial tool for approximating the behavior of a HEMT and can simplify the modeling process by reducing the need for complex analytical calculations[48]. However, Lookup tables have limited resolution, which means they can only provide precomputed values for a finite set of input values. This can result in inaccuracies if the input values fall outside the table's range. They can also be memory-intensive, and if the interpolation method used is not appropriate, interpolation errors can occur. Lookup tables can be difficult to maintain, requiring updates if the underlying function changes, and can add complexity to a system.

2.2.2 Empirical model

Due to their high modeling accuracy and satisfying simulation convergence, empirical models have seen significant success in the last few decades for industrial applications. Though, this model's complexity tends to steadily and significantly rise in order to account for constantly changing material systems and capture all relevant dispersion effects, such as charge trapping and self-heating[49]. Empirical models can be complex, and introducing too many empirical parameters can lead to over fitting and non-physical simulation results. Balancing the model's accuracy and complexity is a challenge in empirical modeling. Several fitting parameters, which must be extracted using experimental data, are used in models like the one proposed by Angelov *et al*.[50] for precise empirical computations. The goal is to include enough empirical parameters to capture the relevant physics or relationships in the data. This requires careful analysis of the data and an understanding of the underlying physics or mechanisms that govern the system being modeled.

2.3 Small signal equivalent circuit model (SSEC)

Extracting a small-signal equivalent circuit is essential for accurate device modeling, requiring expertise in semiconductor physics, circuit theory, measurement techniques, and software tools. The equivalent circuit elements are derived from S-parameters, measured using a VNA. Balancing accuracy and complexity are key; more circuit elements increase accuracy but also complexity[51,21]. Fig. 3 depicts

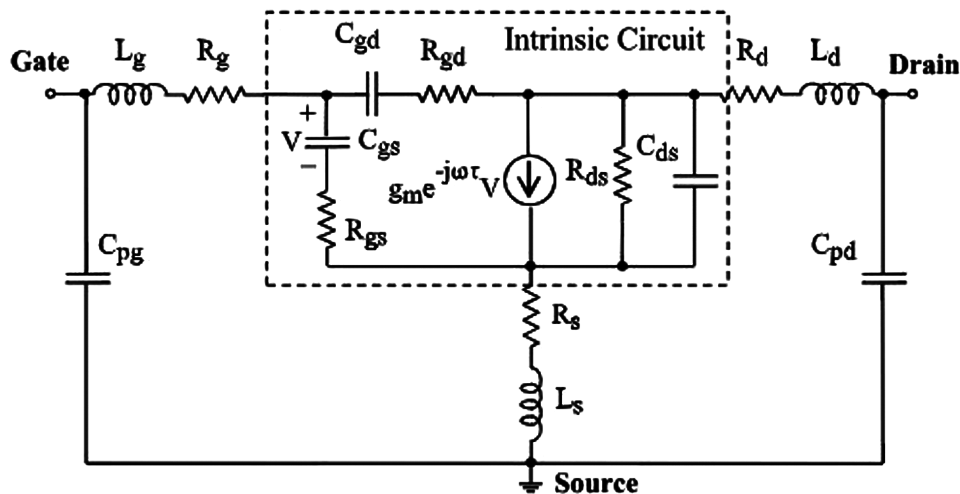

Fig 3 — Small signal equivalent circuit and schematic cross section of GaN HEMT

a typical topology for a small signal equivalent circuit as well as a cross-sectional view of an on-wafer HEMT to illustrate the meaning of each ECP from a physical standpoint.

One of the most widely used bias conditions for obtaining FET small-signal models is known as Cold FET modeling. It is important to note that small-signal equivalent circuits must undergo rigorous validation before they can be considered reliable. The extracted models should accurately replicate the behavior of the device across a wide range of operating conditions. Under cold-FET conditions, a basic small-signal extraction method, first introduced by Diamand & Laviron in 1982, can be employed to derive parasitic inductances and resistances. Additionally, Dambrine *et al*. proposed an analytical approach to compute the intrinsic parameters[52], and further enhanced by Berroth and Bosch. After that many extraction methods have been reported and applied to GaN and Gallium Arsenide devices (Berroth and Bosch[53], Brady, Oxley & Brazil[17], Cheng, Han, Zhai, Sun & Gao[54]; Chen, Kumar, Schwindt & Adesida[55], Crupi *et al*.[15], Santo & Bolognesi[56], Jarndal & Kompa[16], Mishra[57], Khusro[58]). The intrinsic model parameters are then estimated by fitting data from the de-embedded measurements. These estimated model parameters are subsequently used to match the measured S-parameters. This process is iterated to determine the optimal model parameters[59]. The flow diagram is shown in the Fig. 4.

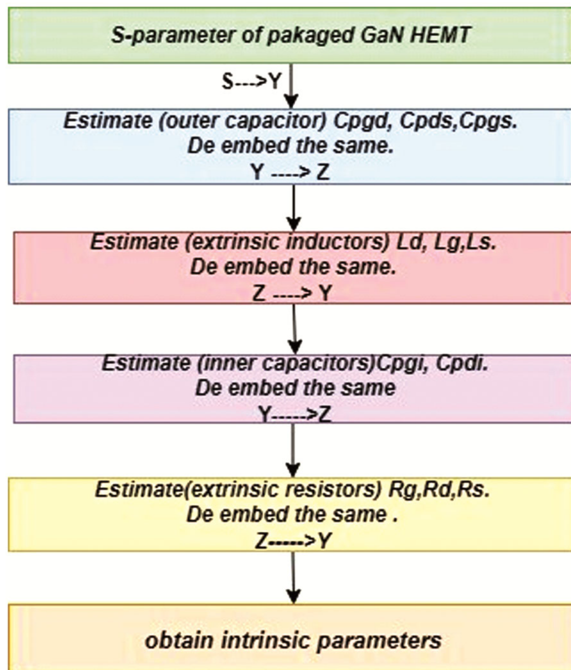

Fig 4 — Flow diagram for parameter extraction

GaN HEMT is an excellent choice for this research because it enables the extraction of additional parasitic ECPs under "cold" conditions with positive V_{gs}. GaN HEMT, compared to GaAs HEMT, is capable of biassing to higher V_{gs} without degrading. Overall, the choice of modeling approach depends on the specific requirements of the application, the available resources, and the level of accuracy needed. It is often useful to combine multiple modeling approaches to gain a more comprehensive understanding of the device's behavior. Although the Cold FET modeling approach has its advantages, it is not without its limitations. One issue with the method is that the assumption that the FET is operating under a "cold" condition, which means that there isn't any electron injection from the source to the channel, is one disadvantage of Cold FET modelling. The FET is never completely "cold" in real-world applications; rather, there is always a certain amount of electron injection from the source. As a result, the Cold FET model's extracted parasitic parameters might not accurately represent the FET's behavior under real-world operating conditions, which could result in errors in the circuit's overall performance. As a result, it's crucial to consider the Cold FET model's limitations carefully and to verify the extracted parameters under actual operating circumstances.

To address this concern, it may be necessary to explore alternative modeling techniques that can provide a more accurate representation of FET behavior under real-world operating conditions. By doing so, it may be possible to improve the overall accuracy of circuit simulations and enable better optimization of circuit designs. Fig. 5 summarizes the common limitations found in traditional approaches[60]. The compilation highlights the critical areas where conventional methods fall short, emphasizing the importance of novel approaches to overcome these challenges."

3 Machine Learning in modelling

Machine learning is a the subdiscipline of Artificial Intelligence, as shown in Fig. 6, attempts to reproduce human brains' thinking. Machine Learning (ML) is a subset of AI that uses algorithms to learn patterns[61].

It can be broadly defined as computational methods to improve performance or to make accurate predictions using past information available to the learner, which takes the form of electronic data collected and made available for analysis They are used for tasks like classification, regression, clustering,

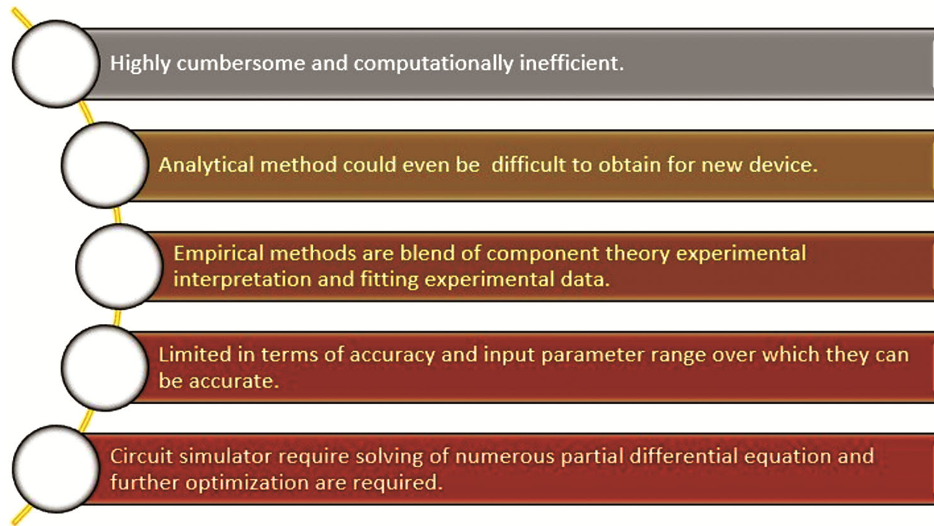

Fig 5 — Comprehensive Overview of Drawbacks Associated with Conventional Methods.

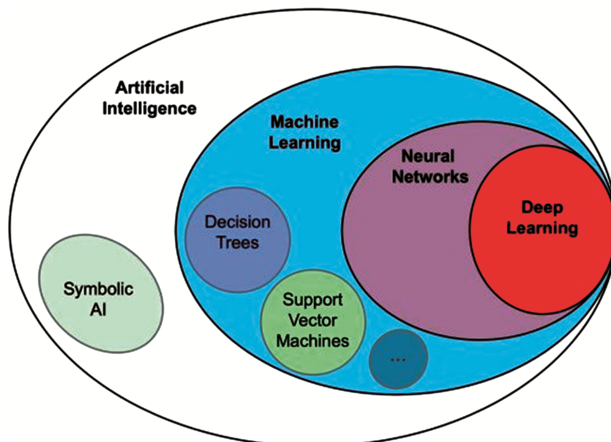

Fig 6 — Taxonomy of Artificial intelligence[62]

and more, by training on a dataset to make predictions or decisions without being explicitly programmed for specific tasks. ML models can be categorized into supervised learning (e.g., linear regression, decision trees), unsupervised learning (e.g., k-means clustering), and ensemble methods (e.g., random forests, boosting algorithms). Algorithms for ML have numerous applications, such as image recognition, natural language processing, speech recognition, autonomous vehicles, etc. To achieve these objectives, as shown in Fig. 7 DT, SVM, neural networks, and deep learning models are among the frequently utilized ML algorithms[63].

Supervised learning for regression involves training a model to predict an output variable (target) from input features (predictors). The model is trained on labeled data, where input features and corresponding output values are provided[64].

During training, the model learns to map inputs to outputs, optimizing this mapping by minimizing a loss function, such as mean squared error (MSE) or mean absolute error (MAE). The flow is shown through Fig. 8. This process helps the model make accurate predictions on new data. Plenty of optimization methods are used to minimize the loss function, refining the model's parameters to best fit the training data[65,66]. ML techniques have gained popularity in recent years as an effective alternative to conventional methods for modeling devices, extracting parameters, and estimating power[67]. Researchers have investigated several ML algorithms to model devices, including ANN, with various optimization techniques presented by Senel *et al.*[68] and SVR with PSO proposed by Khusro *et al.*[32,69]. Due to its quick learning, ability to generalize, robustness to noise, and capacity for handling large amounts of data, numerous nodes, and complex functions, ANN is a widely used mathematical approach for modeling RF and microwave devices[70]. One of ANN's key advantages is its capacity for long training under conditions of high data load, which is why transistor modeling problems are increasingly choosing to use it. Without requiring an in-depth understanding of the system's inner workings, these ML-based techniques enable accurate device models to be generated with increased efficiency and precision, enabling the development of more advanced and optimized devices. This can save time and resources, especially when collecting data on a system's internal mechanisms is difficult or expensive. ML can be used to optimize circuit layout, reduce power consumption, boost yield rates, and detect

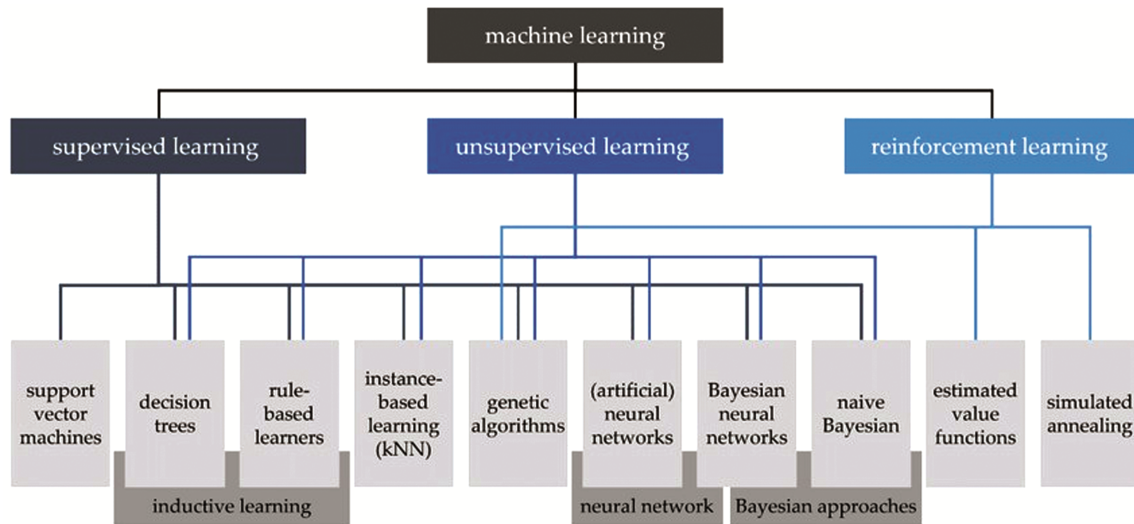

Fig 7 — Types of ML[63]

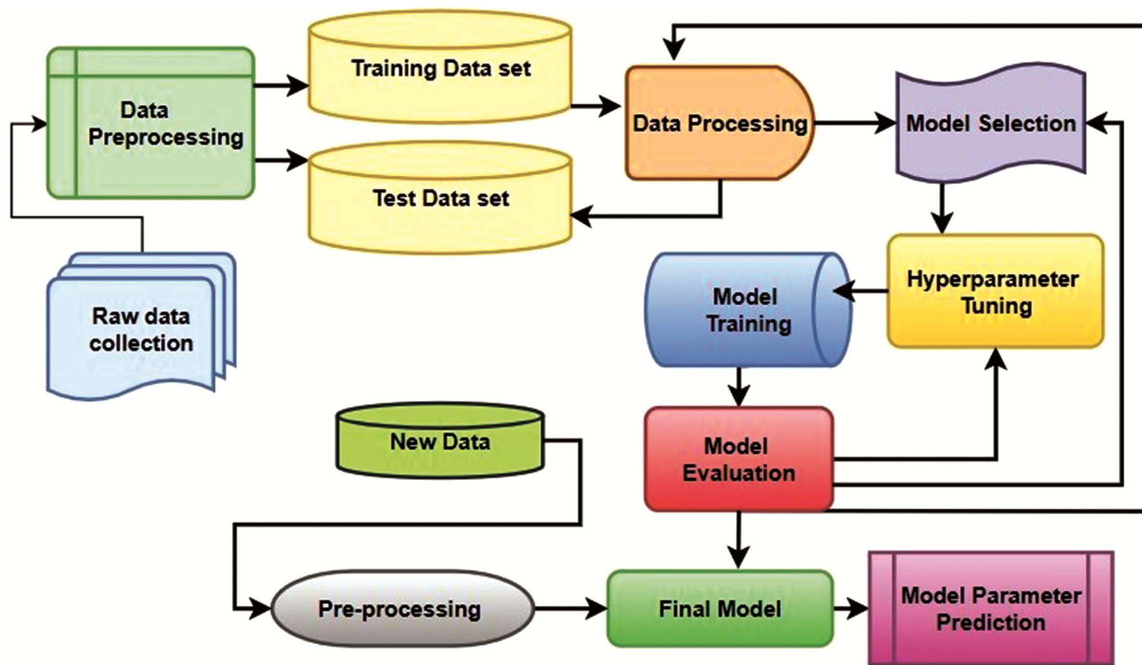

Fig 8 — Basic Workflow of machine learning for model prediction

defects[71]. It can also analyze large amounts of manufacturing data to find patterns that improve quality and efficiency. To compete in a complex and fast-paced market, many electronics and semiconductor companies are investing in machine learning research and development.

4 Review Methodology

This review paper examined ML applications in HEMT modelling. IEEE Xplore, ACM digital libraries, Science Direct, and Wiley Online Library were used to search the literature. The search terms included "small signal modelling", "machine learning," "HEMT modelling," "neural networks," and others. Selecting relevant papers required strict inclusion and exclusion criteria. ML-based HEMT modelling papers in English from reputable journals or conferences were the focus. Novel methods, practical applications, and field impact were prioritized. Traditional HEMT modelling papers were excluded. More than 25 papers covering small signal modelling of HEMT using ML techniques were

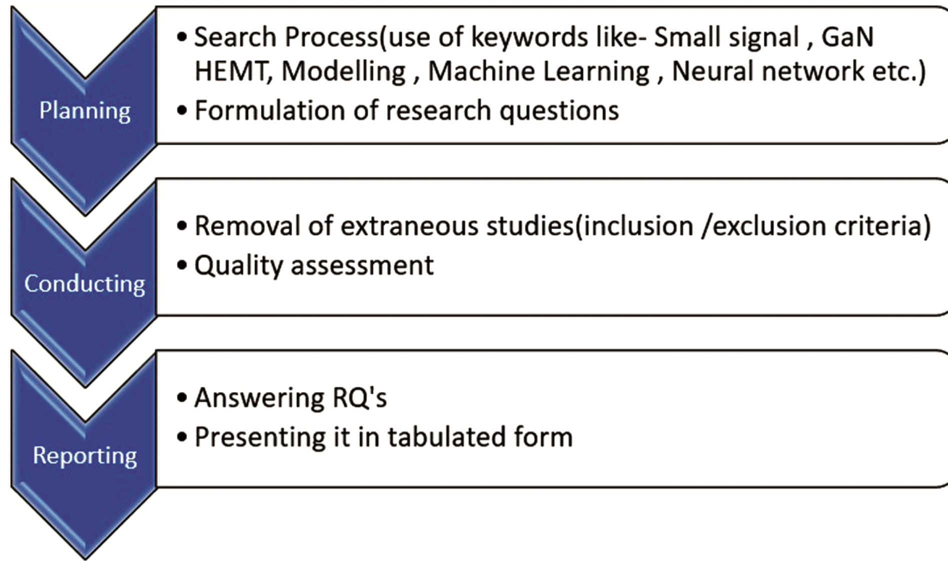

Fig 9 — Review process

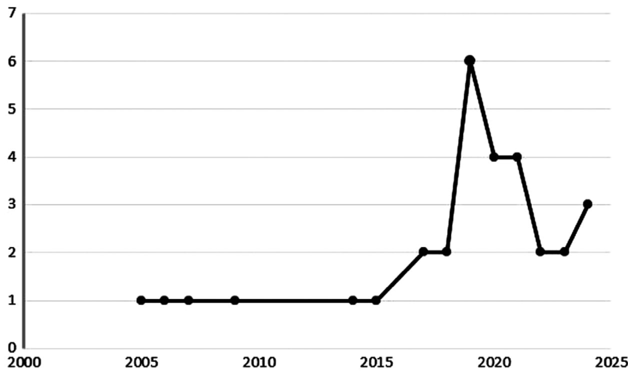

Fig 10 — Trend of research publication for ML-based small signal modelling of GaN HEMT

Table 2 — Quality assessment questions for the literature considered under review

S. no.	Quality assessment questions
Q. 1	Does the study define the aim or objective well?
Q. 2	Does the study based on HEMT modelling?
Q. 3	Is the device for studying GaN HEMT?
Q. 4	Does the study include small signal modelling?
Q. 5	Does the study focus on behavioral modeling?
Q. 6	Does the paper apply machine learning to HEMT modelling?
Q. 7	Whether the dataset sources were indicated?
Q. 8	Whether appropriate results were provided in the study?
Q. 7	Is the Methodology Sound?
Q. 8	Are the Results Reliable and Valid?

selected. HEMT modelling was covered in circuit design optimisation, nonlinear circuit simulation, device characterization, and material/process optimization. These papers came from respected electronics, machine learning, and computational modelling journals, conference proceedings, and technical reports. Each paper’s title, authors, publication year, ML techniques, datasets, key findings, and HEMT modelling implications were extracted. HEMT modelling ML trends, strengths, and weaknesses were identified by analysing the extracted data. Fig. 9 provides the way the review process has been carried out. This synthesis gave a complete field picture and revealed new research directions. Like any review, this study has limitations. Some papers that did not meet the criteria may have been accidentally excluded due to bias in paper selection. Figure 10 shows the distribution of studies and papers that qualify the RQs and are considered for the detailed review. It can be seen maximum literature available and taken for studies is after 2018 so we can say that this is a growing domain and is left to explore more.

As can be seen in Table 2, a questionnaire was designed to aid in the elimination of unnecessary papers and the refinement of assessment and selection of applicable studies.

5 Literature Review

This section shows a comprehensive analysis of selected papers on small signal HEMT modelling based on ML. These papers represent a variety of research efforts aimed at advancing the understanding of HEMT behaviour and optimising circuit design by employing ML techniques. The summary of each paper’s key findings, methodologies, and contributions

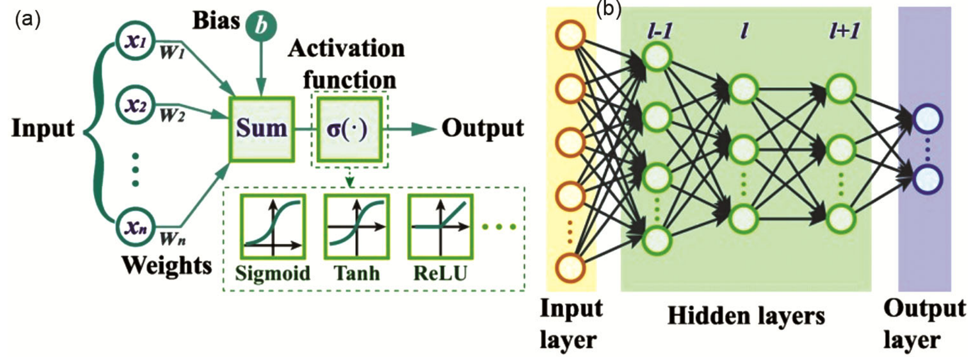

Fig 11 — (a) Neural networks operation (b) Architecture of neural networks[73].

sheds light on the collective impact of machine learning in this field. Through this review, we hope to highlight common trends, strengths, and limitations and identify promising research and application avenues for the future. It is evident that a few research groups are working on GaN HEMT modeling using ML techniques and that new methods and techniques have continuously evolved over the years. The papers are segregated under a technique heading, and key findings are reported as follows:

- **ANN-based:** Artificial Neural Networks (ANNs) are computational models inspired by the human brain, consisting of layers of interconnected nodes or "neurons". The architecture of ANN is given in Fig. 11. These layers include an input layer that receives data, one or more hidden layers that extract features, and an output layer that provides the final prediction. ANNs learn by adjusting the weights of connections between neurons, optimizing them to minimize the difference between predicted and actual outputs using techniques like gradient descent. This learning process allows ANNs to model complex patterns and relationships in data[72].

  In Marinkovic[74] developed a hybrid model, this paper presents two models: A Hybrid neural network model comprising equivalent circuit parameters and neural network, while the second model is a purely black box model. The frequency used is 6-18 GHz. The model predicts signal and noise performances. The proposed model is developed to reduce the complexity of noise measurement in terms of equipment and procedures. Later, the same author[75] in 2006 proposed transistor's gate-width to be an additional input into the neural models. Two subnets of ANN were created for the s-parameter and noise parameter taking input as Gate width of 400um, 800um, and 1600um, V_{ds}, I_{ds}, freq, and Output as ANN1: all 8 S-parameters, and output of ANN2: "minimum noise figure, optimum source reflection coefficient, angle optimum source coefficient, normalized equivalent noise resistance". The model proposed shows accuracy in terms of average test error (ATE), worst-case error (WCE), and correlation coefficient (WCE). For noise parameters. ATE: 0.7% for training and 2.6% for testing. WCE: less than 5.41% for scattering parameters. ATE:2% WCE: 8.5% Both the devices show good agreement. Initially, values for the signal and noise parameters of the transistor were determined across various temperatures within its operating range. This process was repeated across the operating frequency range. The measured data was then used to derive accurate values for the equivalent circuit parameters (ECPs) at each temperature point. Neural networks were trained on this data, and the ECP temperature dependence was successfully learned, as shown in the graphs. Later, along with frequency, gate width, and biases were fed into a model to generate 8 S-parameters and 4 noise parameters — a hybrid approach. Subsequently, a black box model was developed, which showed better results than the hybrid model. The paper demonstrated that ANNs outperform ECPs due to the latter's complex and time-consuming parameter extraction process across various temperatures. In Caddemi *et al.*[76] presented cryogenic modeling of HEMT. DC and RF characterization of HEMT is done at the temp of 70K. Input for the DC model was taken as V_{ds} (0-2.5V), V_{gs}(0-.6V), and temperature (220 K to 70 K), and Ids(0-31.6mA) is taken as output. The

frequency range used for RF characterization was .05-6 GHz. In this paper, 3 ANN models are used to model HEMT, 2 for magnitude and phase of S-parameter, respectively, and 1 for Ids. They are then compared with measured data. The results show close accuracy between the measured and proposed ANN model data. Overall, the paper demonstrates a successful application of ANN for developing a HEMT model with the potential for use in circuit and system design. In Marinkovic[77] made a comparative study of modeling using the analytical model and ANN-based model. The proposed model is an improvement of the above paper[75]. In this paper, a small signal, the equivalent circuit, is built using the conventional method of parameter extraction technique through the cold FET pinch-off technique. 8 extrinsic and 8 intrinsic parameters are extracted. secondly, the ANN model is built using gate width (100um, 200um, 300um), V_{gs}(1.5-0V), V_{ds}(0-2.5V), and freq (.5-50GHz) as input parameters and S- parameter as output Both methods showed good accuracy, showing percentage error as follows: ANN model: min error 1.7% and max error 9.5% The paper concludes both methods show good accuracy, and ANN model could be used where only knowledge of behavior is required, whereas when knowledge of the device physics is required analytical model could be used. thereafter in 2014 they[78] proposed temperature-dependent modeling of GaN HEMT for the frequency range 0.3-40GHz and taking five different temperature points 20,35,50,65 and 80 (Celsius) and showed temperature-dependent S-parameter modeling with biases along with V_{ds} (0-28V), V_{gs}(-6-0V). Two models were developed, one taking linear frequency as input and the other with logarithmic frequency for S_{21} as GaN HEMTs can reach very high values of the magnitude of S_{21}, and hence, to make dynamics of the S_{21} magnitude smaller, the logarithmic scale was used for both S_{21} magnitude and frequency. The gate has a length of 0.7 um and a width of 800 um, with two fingers each measuring 400 um. Different numbers of hidden neurons for each output parameter, refer to Table 1 of the paper. After training and testing both the created models show close accuracy with the experimental data. Furthermore, a good agreement between MAG and MSG and the stability factor which has been calculated from measured and simulated data. The average percentage of error is lower than 3% and the max value is lower than 6% for the training set. The table shown in the paper shows percentage error at all temperature points. Due to the space constraint, it is challenging to fit all the results in the available space.

Dordevic *et al*.[79] demonstrated a neural approach for extracting noise model parameters by avoiding optimizations. The frequency range used is 6-18 GHz over the temperature range of 233K-333K. This paper aims at avoiding time-consuming optimization procedures in microwave circuit simulators, that are frequently used to determine noise model parameters. The technique uses 2 ANN models and the output of the first is noise intrinsic parameters is fed to the second ANN model to get equivalent noise drain temperature. noise models for which extraction is performed are the Noise wave model and Pospieszalki's model. When the need arises to repeat the extraction for a greater range of operational points, the suggested model is frequently more effective than conventional optimization techniques. The graph (Fig 5 in ref) demonstrates good precision with the measured samples.

In Marinkovic[26] used ANN to model several types of FET devices, GaN HEMTs, GaAs HEMTs, Si FinFETs, Si FinFET varactors, and Si MOSFET Small signal S-parameter for frequency range 5 to 50GHz. S-parameter modelling done for various FETs; it was found: Critical analysis of various semiconductor devices reveals distinct approaches in ANN modeling. For GaAs HEMTs, a single ANN effectively models all S-parameters within a narrow bias range, while separate ANNs are necessary for the real and imaginary parts of S-parameters across a wider bias spectrum. In contrast, GaN HEMTs, characterized by high S21 magnitude, benefit from a logarithmic representation to enhance ANN performance. Si FinFETs employ a two-step model using prior knowledge input (PKI) neural techniques to address low-frequency kinks, demonstrating a nuanced approach tailored to device characteristics. Si FinFET varactors, due to their symmetric and reciprocal nature, require separate models for S11 and S22, focusing solely on these parameters. Lastly, Si MOSFETs utilize a bias-dependent neural model scalable with gate length, employing separate ANNs to accurately capture the real and imaginary components of each S-parameter, reflecting the complexity of modeling in these devices. Later compared with that of the measured data and error calculated are as

shown:(average error of all four S -parameters)GaAs HEMT: less than 5% GaN HEMT: less than 3% (the measured and predicted value are plotted and represented as by as shown by the Fig. 12(a) Si FinFET: min error 3% and max error 5% FinFET varactor: 2.2% but significantly for S_{22} its 20% to 40% Si MOSFET: less than 1% and for S_{21} its less than 2.6% The paper concludes that neural model strongly depends on device's technology. Khusro[29] in did ANN-based HEMT device Behavioral modeling of 2 × 200µm GaN (HEMT) using two different architectures MLP and cascade feed-forward. RF characteristics were studied for the structures and compared based on accuracy, convergence rate, and generalization capability. Input were V_{gs} (-7 to 0V), V_{ds} (0 to 10V), and freq(1-18GHz). Output was 8 S-parameters. To ensure robustness, the proposed model is tested for accuracy, convergence rate, time elapsed, and generalization under various training algorithms, activation functions, hidden layer count, neuron embedding, weight and bias initialization methods, and other key parameters affecting accuracy and effectiveness. The analysis determines device modeling parameters and MLP and cascaded MLP architectures have similar accuracy. Cascaded MLP architecture requires more iterations and convergence time. Husain *et al*.[36] performed a deep dive into six distinct ANN architectures used in the creation of a small-signal model for GaN HEMTs 4 × 100µm. Input were V_{gs} (-7 to 0V), V_{ds} (0 to 10V), and freq (1-18GHz). Output was 8 S-parameters. In a comparative study of neural network architectures, both MLP and Cascade MLP demonstrated strong performance, with the Cascade MLP slightly outperforming due to its additional weight connections. The NARX-SP architecture excelled, outperforming all others due to its ability to learn from both input and true output data, whereas the NARX-P architecture showed inferior performance. Distributed Delay and Layer Recurrent Networks were less effective, with the Layer Recurrent Network exhibiting the poorest performance among the tested architectures. Hussain *et al*.[30]. The study employs a comprehensive approach to develop and evaluate ML-based SSMs for GaN HEMTs, encompassing data preprocessing, model development using various ML algorithms, hyper parameter tuning with Random Search Optimization (RSO) and 5-fold cross-validation, and model evaluation on unseen testing sets. Output are 8 S-parameter and Input taken are V_{gs} -7 to 0 V, V_{ds} 0 to 10 V, freq 1 GHz to 18 GHz number of Figs. 2,4 and gate width 200 um, 100 um. Evaluation metrics include generalization capability, computational efficiency, training and simulation time, model capacity, and parameter tuning time. The findings reveal that ANN and GA-ANN models demonstrate superior generalization capability and accuracy, with GA-ANN slightly outperforming ANN due to better weight initialization. Graphical representation is provided by the Fig. 12(b). The RANSAC model, while computationally efficient, is less accurate, particularly for phase predictions, due to its reliance on linear decision boundaries. SVR and GPR models perform well with smaller datasets but are computationally expensive and less accurate with larger, noisy datasets. Decision tree and ensemble models, including Random Forests (RFs), Extremely Randomized Trees (ERTs), and Gradient Boosting methods, provide robust and efficient modeling solutions, with XGBoost exhibiting notable performance. Due to space constraints, graphical results are presented for only two sample papers. Readers are encouraged to refer to the cited articles for a more comprehensive

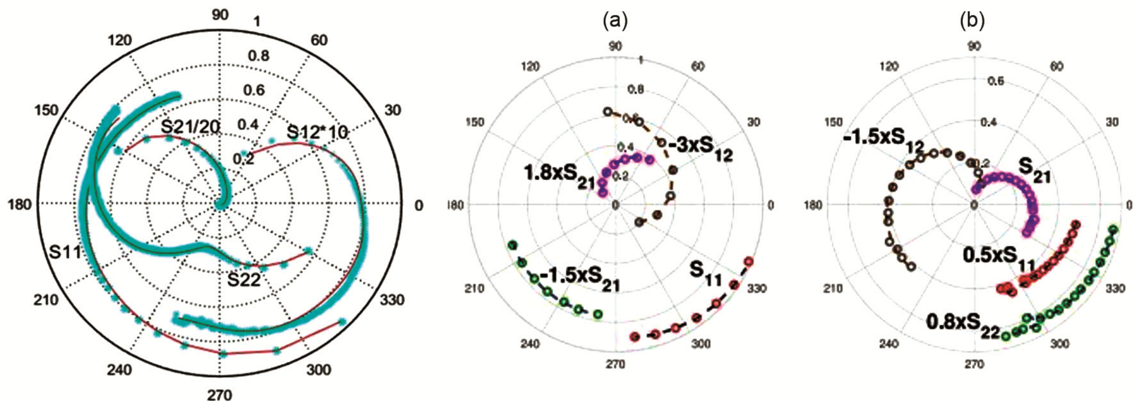

Fig 12 — Predicted and measured S-parameters represented from two literatures

analysis. Husain *et al.*[80] presented a paper analyzing the platform best for modelling GaN HEMT employing ANN-based models developed in MATLAB, Python (using Keras, PyTorch, and Scikit-learn), and R (using the H2O package) to model GaN HEMTs, using datasets from GaN-on-Diamond and GaN-on-Si HEMTs. The models were evaluated based on Mean Squared Error (MSE), Mean Absolute Error (MAE), and R^2. They were also assessed for CAD tool compatibility, generalization capability, training and prediction speed, and user-friendliness of the development environments. All models demonstrated high accuracy with low MSE and MAE values and high R^2 scores. MATLAB and Python models integrated seamlessly with CAD tools like Keysight ADS, and all models showed strong generalization capabilities. MATLAB and R (H2O) models were more time-efficient, with PyTorch showing the fastest training speed among Python frameworks. MATLAB and Python were noted for their user-friendly interfaces and extensive support, while R provided a robust, albeit less intuitive, development environment. Table 3 refers to the critical analysis of ANN based models mentioned in the text. ”NM” in the table refers to where samples are not mentioned.

- **Support Vector Regression /SVM based:** SVM regression or SVR is a regression analysis ML algorithm. It finds a hyperplane that best fits the data points in a continuous space, unlike linear regression, which fits a line. An SVR algorithm finds the hyperplane that passes through the most data points within a margin. This method reduces prediction error and lets SVR handle non-linear input-target relationships using a kernel function. Thus, SVM regression is useful for regression tasks with complex input-target relationships[81]. Khusro[82] in provided with Modeling of a 4x100μm GaN HEMT over frequency ranging from 1-18 GHz using SVR. In this paper, the author explores a new method called SVR to model device responses to small signals. Model is based on input (V_{ds}, V_{gs}, Freq) and output (s-parameters) The technique has been shown to model the performance of the device very accurately, which is clear from how well the modeled performance and measured data match up. ANN, SVM and DT-based paper by Abubakr[83] in proposed nonlinear modeling of GaN150 HEMT for I-V characteristics based on input parameters V_{ds}(0-15V), V_{gs} (-5 to 0V), and temperature ranging from (25-250 Celsius). Three models were built using ANN, SVR, and DT. The paper proposes three data-driven models for I-V characteristics. All three models are built using the ML technique in MATLAB. Based on MSE, the accuracy of the model is determined. The model was trained and tested at different bias points and ranges of temperatures and later validated with experimental data. For accuracy, MSE is considered and shows the following results. ANN model: $1.3 * 10^{-7}$ SVR model: $6.6 * 10^{-8}$ DT model: $6.3 * 10^{-8}$. The SVR model is best in terms of accuracy while ANN is best in case of generalization. Khusro[84] By using two distinct geometries of 2×200μm and 4×100 μm of GaN HEMT .The model demonstrates high accuracy and computational efficiency by accurately predicting intrinsic parameters with low mean square error and epsilon-insensitive loss. Input to the model was V_{ds} (0 to 10V), V_{gs} (-7 to 0V), freq (1 to 18Ghz), Number of fingers (2,4) and gate width and ten intrinsic parameters generated as output. It effectively handles variations in frequency and bias conditions, showing a slight dependency of intrinsic parameters on these factors. Geng *et al.*[85] paper focuses on the comparison of the piecewise ECP model and the proposed piecewise SVR-based model. The device is 8 × 125 um GaN HEMT

Table 3 — Critical Analysis of ANN-based Models

Ref	Input	output	no. of samples	Hidden neuron
[74]	Temp, freq	8-S-parameter, 4-Noise parameter	NM	10
[75]	Gate width, Ids, V_{ds}, freq	8-S-parameter, 4-Noise parameter	NM	8 and 7
[76]	V_{gs}, V_{ds}, T, freq	8-S-parameter, Ids	546 and 10374	9,26,19
[77]	V_{gs}, V_{ds}, W, freq	8-S-parameter	165438	25-25, (for ImagS12)21-20
[78]	V_{gs}, V_{ds}, T, freq	8-S-parameter	NM	table 1 in ref paper
[79]	ECP (19), N_{total}, T, freq	N_{int} , equivalent drain noise temperature	45000	9-12
[29]	V_{ds}, V_{gs}, freq	8 S-parameter	8640	Study on Hidden Neuron Variations
[36]	V_{ds}, V_{gs}, freq	8 S-parameter	8640	7-7-7
[30]	V_{ds}, V_{gs}, freq, N, W	8 S-parameter	17280	10-10-10,12-12-12
[80]	V_{ds}, V_{gs}, freq and V_{gs}, V_{ds}, freq, T	8 S-parameter	36400 and 103,057	6-6-6 , 8-8-8

with a 0.25 um gate feature size. The proposed model predicts S22 more accurately. The SVR model greatly improves prediction accuracy. In Figure. 7 of the paper, the test device's S12 exhibits strong nonlinearity, yet the SVR model accurately predicts the measured S-parameter, a feat that conventional modelling techniques struggle to achieve. The frequency range taken in this paper is 1 GHz - 10 GHz. The measured S-parameters are divided into real and imaginary parts. The input dataset is created by combining the frequency data with the real and imaginary parts of the S-parameters. Both methods are compared using measured data. SVR shows better results with more accuracy and fewer percentage errors. Later in 2021 a hybrid equivalent circuit/SVR-based propose model[86] for GaN HEMT adds an error correction technique, which is developed using SVR techniques as shown in Fig. 13. The model maintains accuracy for the 1GHz- 10GHz range of frequency.

The simulation demonstrates an equivalent circuit model cascaded with SVR for S-parameter error correction. The error correction process involves utilizing uncorrected parameters' real and imaginary components as inputs. This method effectively improves the overall accuracy and generalizability of a model. Following the fitting of the SVR model, the simulated S-parameters are obtained, and the results are compared with actual measured data. However, with this change, the model complexity slightly increases, and the accuracy increases as well. Khusro[32] in explored PSO-tuned SVR small-signal behavioral modelling of GaN HEMTs. The model inputs are V_{ds} (0 to 10V), V_{gs} (-7 to 0V), freq (1 to 18Ghz), Number of fingers (2,4), and gate width (200um and 100um), while the outputs are the device's RF performance S-parameters (S11, S22, S12, S21). The model was developed and validated using 11520 training and 5760 testing samples. The PSO-SVR model's mean relative error (MRE) of 1.5-3.5% for frequency extrapolation, robustness to noise effects, and superior prediction accuracy and generalization compared to conventional ANN-based models are key findings. Integrating the model into CAD for circuit simulation and analysis, such as stability and gain tests for power amplifier designs, showed its utility. Jarndal[42] in explored HEMT modeling methods using "GA, ANN, and PSO with SVR". A promising large-signal modeling technique based on Gaussian Process Regression (GPR) is also discussed. Thereafter, in 2021 the author gave paper[87] which used ANN and SVR for GaN-on-Si HEMT modeling technique used for small signal modeling, The study employs two machine learning techniques, ANN and SVR, to model the temperature-dependent small-signal behavior of GaN-on-Si HEMT. The ANN model uses a multilayer perceptron architecture, while the SVR model utilizes Gaussian kernel functions. Both models are trained on a large dataset from a GaN-on-silicon device with V_{gs} (-2 V to 2 V), V_{ds} (-2 V to -0.4 V) and (-2 V to -0.8 V), Ambient Temperature (T) (25 to 175 °C) with a step size of 25 °C, and Freq (0.1 GHz to 20 GHz), with particle swarm optimization (PSO) integrated to enhance performance. Findings indicate that the ANN model demonstrates superior prediction capability and faster convergence, with PSO significantly improving accuracy and robustness for both interpolation and extrapolation. The SVR model offers robustness against local minima and is less sensitive to initial conditions, but its performance depends heavily on the careful tuning of hyperparameters, which is achieved using PSO.

- **Decision Tree based[88]*:*** In Khusro[89] provided Behavioral modeling of a 4x100 μm GaN HEMT over a broad frequency range of 1-18 GHz using a decision tree. Model is based on input V_{gs} (-7V,0V) and V_{ds} (0V, 10V) and output as all real and imaginary s-parameters. A comparison table is

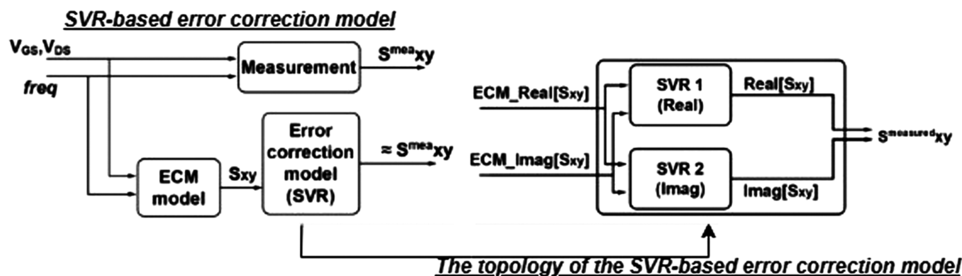

Fig 13 — proposed model by[86]

made for comparing ANN, SVR, and DT based on Mean square error (MSE). The suggested model is more generalizable and accurate than SVR and ANN for the provided frequency range and multiple bias conditions. The proposed model and the measured S-parameters are in agreement. As we know random forest is an ensemble learning method that combines multiple decision trees to improve accuracy, robustness, and generalization by averaging their predictions and reducing overfitting. In Mishra[31] provided a cross-platform application that predicts GaN HEMT devices scattering (S-) parameter, gain, power, device width, and traps. For 0.5–100 GHz frequencies, a hybrid multilayer perceptron random forest (RF) model is created. Classification and Regression are both performed for the device modeling. Case 1: A 13-input regression model is used for predicting S-parameters and current gain, with inputs: Frequency (500 MHz to 100 GHz), V_{ds} (0 to 19V), IDS (0 to -6 V), V_{gs}, CSS, CDS, CGS, CSD, CDD, CGD, CSG, CDG, and CGG. Case 2: The same 13-input classification model predicts device width based on width type. Case 3: The same 13-input classification model predicts device traps based on trap type. Case 4: A separate regression model predicts power metrics (POUT, gain, and PAE) using inputs: frequency, real and imaginary parts of S11, S12, S21, S22, V_{ds}, IDS, V_{gs}, and PIN. The study's findings reveal that the model achieves over 99% accuracy in predicting S-parameters and current gain across a wide frequency range (500 MHz to 100 GHz), with high precision indicated by low mean absolute error (MAE) and mean squared error (MSE) values. It demonstrates excellent classification accuracy for device width, with a prediction probability exceeding 88% over multiple iterations. Additionally, the model accurately classifies different trap types within the device, capturing subtle device physics. For power estimation, it predicts key metrics such as output power, gain, and power-added efficiency with an error margin of less than 10%, validating its applicability for circuit-level analysis.

- **Genetic Algorithm based:** In 2017 A genetic algorithm in machine learning is a search heuristic that mimics natural selection to optimize solutions. It involves initializing a population of potential solutions, evaluating their fitness, and iteratively applying selection, crossover, and mutation to evolve better solutions. This method is useful for optimizing hyperparameters, feature selection, and neural network architectures[90]. Ahmed S. Hussein came up with Hybrid optimization of parameters using different optimization techniques such as GA, PSO, and Artificial Bee Colony (ABC)[69]. Extrinsic parameter extraction and S-parameter simulation, comparison table between all three optimization techniques. Sometimes at higher frequencies, parameter extraction becomes tedious as more parasitic elements are required which makes the circuit complex, so in this paper, the author has applied tuning or optimizing the extrinsic parameter using a ML algorithm that can provide the expected results. The main findings indicate that PSO requires fewer iterations and shorter execution times, making it the most efficient and robust technique among the three. The extracted parameters are validated through S-parameter fitting, confirming the reliability of the extraction procedure. The input parameters include the measured S-parameters, while the output parameters are the optimized model parameters for the GaN HEMT device Jarndal[91] in focused on optimization techniques used with ANN namely GA, PSO, and GWO. And comparing the optimized results with the measured data and comparing different optimization techniques. This was not applied for small signal modelling of HEMT but it could be applied and analyzed for the GaN HEMT modelling. Jarndal explored[42]. The paper makes significant contributions to GaN HEMT modeling techniques by introducing GA-augmented ANN and PSO-augmented SVR models, which address local minima issues in ANN training and reduce optimization variables, resulting in robust and efficient models. It also presents Gaussian Process Regression (GPR) as a new, probabilistic approach to model drain and gate currents, offering a good balance between accuracy and simulation time. Input to the model is V_{gs} and V_{ds}. The developed models are validated using large-signal measurements of a 2-mm GaN device, with a comprehensive comparison showing the strengths and limitations of GA-ANN, PSO-SVR, and GPR models in terms of mean squared error and simulation time. The models are practical and efficient, suitable for use in commercial CAD tools, and demonstrate a significant reduction in simulation time and higher

convergence rates compared to conventional techniques, making them valuable for designing high-power and high-frequency devices in advanced broadcasting and communication systems. In Jarndal[92] this paper addressed the challenge of accurately modeling the temperature dependence of GaN HEMTs, crucial for RF and microwave circuit design due to their high electron mobility and saturation velocity. The study employs Multilayer Perceptron (MLP) and Cascaded MLP architectures, optimized using GA to improve robustness and accuracy by addressing issues of overfitting and local minima. Trained and tested across a range of bias voltages: *Vgs* (-2 to 2V), *Vds* at specific points (7 V, 28 V, and 48 V), ambient temperatures (25 to 175 Celsius), and frequencies (0.1 to 20 GHz), the models show excellent agreement with measured S-parameters, validating their accuracy for both interpolation and extrapolation. While the GA-augmented Cascaded MLP offers superior performance, it comes with increased complexity. The proposed model flow diagram is shown through the Fig. 14. The study concludes that GA-initialized ANN models, especially the Cascaded MLP, provide an efficient and robust method for temperature-dependent small-signal modeling of GaN HEMTs, beneficial for high-frequency device modeling where computational efficiency is essential.

- **Other Algorithms and techniques:** Khusro[27] used nonlinear autoregressive exogenous inputs (NARX)-based architectures are to model a 2x200μm device over a wide frequency range of 1GHz to 18GHz and additional input to the model are V_{ds} and V_{gs}. The study explores two NARX-based ANN architectures, series-parallel and parallel, trained using Levenburg-Marquardt (LM), Bayesian regularization (BR), and steepest conjugate gradient (SCG) optimization algorithms. The models were evaluated based on mean square error (MSE), convergence rate, and training epochs. The series-parallel architecture demonstrated higher accuracy and faster convergence, with Bayesian regularization achieving the best accuracy and Levenburg-Marquardt the fastest convergence. Although slightly less accurate, the parallel architecture was effective for multi-step predictions. Model validation against measured S-parameters showed excellent agreement, particularly with the series-parallel model closely matching the phase and magnitude across the frequency range. This paper, authored by Saddam Husain *et al.*[93] in presents the development and deployment of a Gaussian

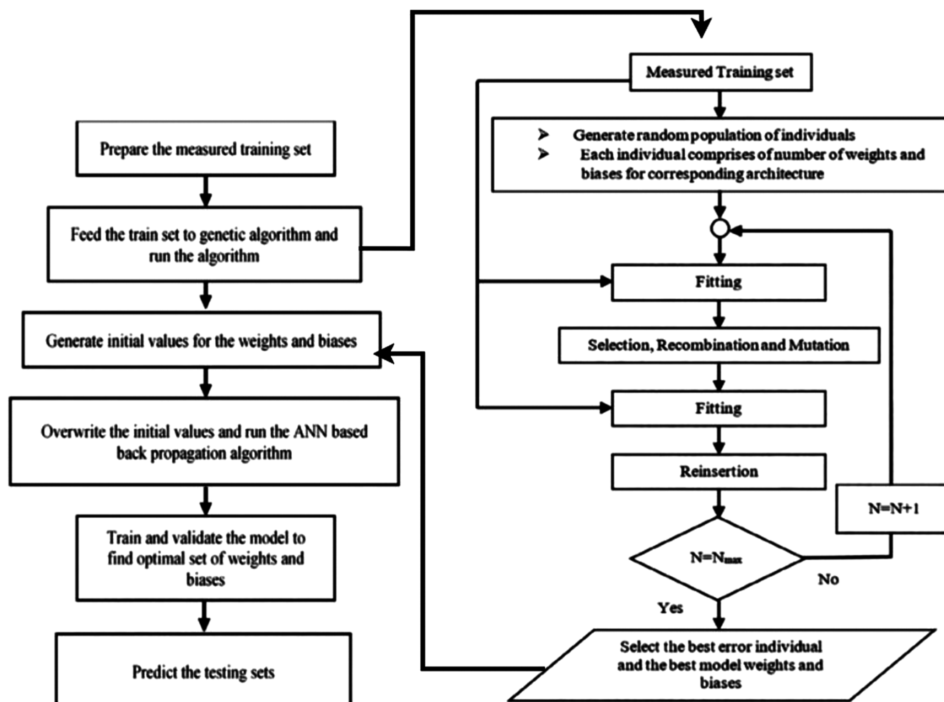

Fig 14 — Flow diagram of Genetic Algorithm based on proposed small signal modelling by[92]

Process Regression (GPR) based small-signal model for Gallium Nitride (GaN) HEMTs within a Computer-Aided Design (CAD) environment. The study addresses the complexities of modeling GaN HEMTs, especially due to self-heating and trapping effects, which are critical for high-speed communication devices. Traditional parameter extraction methods are time-consuming, leading to the adoption of machine learning approaches for more straightforward analysis. The GPR model introduced captures the bias V_{gs} (-7V to 0V), V_{ds} (0V to 10V) and frequency (1GHz to 18GHz) dependence of GaN HEMTs, with advanced preprocessing and hyperparameter tuning validated by 10-fold cross-validation. The model's effectiveness, demonstrated through Mean Squared Error (MSE) metrics, supports its integration into CAD tools, where its stability and application in class-F power amplifier design are tested. The results show excellent gain characteristics, validating the model's practical utility. Compared to other machine learning methods like Artificial Neural Networks (ANNs) and Support Vector Regression (SVR), the GPR model offers robustness and flexibility, making it an efficient solution for small-signal modeling. The paper suggests extending this Bayesian approach to large-signal and electrothermal models for future applications. In Husain[30] The devices used to collect the data are GaN HEMTs with 2x200 um and 4x100 um geometries. Different algorithms, including ANNs, RANdom SAmple Consensus, SVRs, SPRs, DTs, and GA-ANNs, are used to apply the bias-V_{ds} (0to 10V), V_{gs} (-7 to 0V), frequency (1 to 18GHz)-, and geometry-N (2,4) and Wg (100um, 200um) dependent S-parameter small signal modeling technique. After that, the author investigated the capabilities of various ensemble methods, such as Bootstrap aggregation, Random Forests, Extremely Randomized Trees, AdaBoost, GTB, Histogram-based Gradient Boosting, and Extreme Gradient Boosting. To determine the most effective ML-based small-signal modeling, extensive analysis, and comparisons were conducted. Starting with ML algorithms like ANN, RANSAC, SVR, GPR, DT, GA-based ANN, BAM, RFs, ERTs, AdaBoost, GB, HGB, and XGBoost, GaN HEMT modeling frameworks are created. Next, model parameters are optimized for optimal performance. The models are compared based on generalization capability, ADS compatibility, computational efficiency, training and simulation time, model capacity, and parameter tuning time. Model generalization is calculated using MSE, MAE, and R2. GA-initialized ANN models deliver the most accurate small-signal behavior description of GaN HEMT devices. Graphical representation is provided by the Figure 12b Additionally, ANN and XGBoost models exhibit comparable performance. The tree-based models yield excellent results. Results indicate that RANSAC, AdaBoost, SVR, and GPR are unsuitable for modelling GaN devices. Later in Husain *et al.*[94] came up with efficient small-signal model parameter extraction for GaN HEMTs. It introduces a scanning-based systematic approach and hybrid methodologies using the Marine Predators Algorithm (MPA), Pelican Optimization Algorithm (POA), and Tunicate Swarm Algorithm (TSA). The device has been characterized for V_{gs} (-3 V to 0 V), V_{ds} (0 V to 30 V), and freq from 0.1 to 40 GHz. Validation on a GaN HEMT on a diamond substrate demonstrates their strengths and weaknesses. Both approaches achieve excellent agreement with measured S-parameters up to 40 GHz. However, OA-based hybrid modeling is more physically relevant, albeit with increased execution time. The scanning-based method is quicker but relies on assumptions, limiting reliability. MPA and POA have similar accuracy, complexity, and tunable parameters, but require more execution time than TSA.

In Neda *et al.*[95] showed a comparative analysis of 3 ML algorithm viz, MLP with two different activation function and Decision tree and random forest for S-parameter modelling over the same data set. Results showed better accuracy for the Decision tree. Input to the model was freq (10Hz - 60GHz), V_{gs} (-1V, -2V), *Vds* is 12V, 15V. Later in the year article[96] shows the importance of K-fold cross-validation in ML-based modeling. In the article, the author studied 9 ML techniques viz (Multiple Linear Regression, Multivariate Linear Regression, Ridge Regression, Lasso Regression, Elastic Net Regression, RF, GBR, and SVR), using four CV (3, 5, 7, 10) for S-parameter modeling. Predictor variables were V_{gs} (- 4 V to 2 V), V_{ds} (0 V to 16 V), freq (1 to 50 GHz), gate width (200 and 100 um.) it was found that random forest with

10-fold Cross Validation was most accurate with average MSE 4.637510^{-5}.

In a latest study by Cai[97], a novel algorithm, Pelican-Gaussian Process Regression, is explored for modeling the large-signal characteristics of GaN HEMTs. This highlights that the modeling of GaN HEMTs is a highly dynamic and rapidly evolving field, expanding from small-signal to large-signal applications and beyond. However, this review paper focuses specifically on small-signal modeling, providing a solid foundation for new researchers interested in further exploring semiconductor device modeling within the machine learning domain.

As seen in Fig. 15, the most frequently used ML approach for behavioral modeling of GaN HEMT is ANN. The other widely used algorithms are SVR/GA *etc*. and still new approaches are being explored and making the model more accurate and robust. A detailed and precise report is presented in response to the specified RQs. It provides information regarding the ML techniques, dataset, method, and error metrics used to evaluate the model. By doing so, one can determine the areas and circumstances in which these two disciplines might mutually enhance one another. The practical information has been systematically gathered and presented in Table 4.

Table 5 shows a concise summary of the limitations associated with each ML model, helping researchers and engineers identify potential challenges when selecting the appropriate model for GaN HEMT modeling. This table serves as a guide to better understand the trade-offs and limitations of different machine learning approaches.

6 Performance Evaluation Metrics

Researchers assessed the precision of their models through the utilization of various validation approaches and evaluation metrics. The distribution of the most commonly employed evaluation metrics, as reported in our paper pool, is illustrated in Fig. 16. The computation metrics MSE, MAE, and R2, denoted by 1, 2, 3 and 4 are employed[75,36] to evaluate the model's generalization capability, or the precision of the trained ML models on an independent, unseen testing set, respectively.

$$\text{MSE} = \frac{1}{n_{\text{samples}}} \sum_{j=1}^{n_{\text{samples}}} \left(y_j^{\text{meas}} - y_j^{\text{pred}}\right)^2 \quad \text{... (1)}$$

$$\text{MAE} = \frac{1}{n_{\text{samples}}} \sum_{j=1}^{n_{\text{samples}}} \left|y_j^{\text{meas}} - y_j^{\text{pred}}\right| \quad \text{... (2)}$$

$$R^2 = 1 - \frac{\sum_{j=1}^{n_{\text{samples}}} \left(y_j^{\text{meas}} - y_j^{\text{pred}}\right)^2}{\sum_{j=1}^{n_{\text{samples}}} \left(y_j^{\text{meas}} - \bar{y}\right)^2} \quad \text{... (3)}$$

$$\text{(correlation coefficient) } r = \frac{\Sigma(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\Sigma(x_i - \bar{x})^2 \Sigma(y_i - \bar{y})^2}} \quad \text{... (4)}$$

$$\text{where } \bar{y} = \frac{1}{n_{\text{samples}}} \sum_{j=1}^{n_{\text{samples}}} y_j^{\text{meas}}$$

- Accuracy: It's a fundamental metric for measuring the overall accuracy of ML models in predicting HEMT parameters. It provides an initial evaluation of the model's performance by calculating the proportion of correct predictions relative to the total number of predictions.
- Mean Squared Error (MSE) and Root Mean Squared Error (RMSE): MSE evaluates the average squared difference between predicted and actual values, providing insight into the prediction errors of the model in regression tasks. The root square of

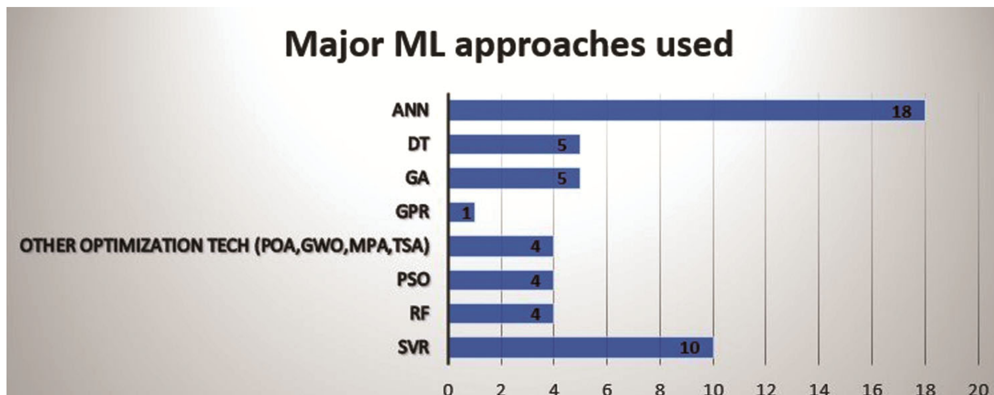

Fig 15 — Frequency of Use of Machine Learning Approaches in Reviewed Literature: Highlighting the Most Commonly and Frequently Applied Techniques

Table 4 — Analysis and precise representation of each model

Year and Author	ML Technique	Evaluation metric	Model characteristic
Caddemi 2007[76]	ANN	Accuracy	cryogenic modeling and accuracy of the model is shown through graphical representation.
Marinkovic 2005 [74]	Hybrid (ECP+ANN)	accuracy	S-parameter and noise parameter modelling
Marinkovic 2006 [75]	MLP- ANN	r,ATE, and WCE	S-parameter and noise parameter modelling of HEMTs
Marinkovic 2009 [77]	ANN	Percentage error	S-parameter modelling and the paper is an improvement of the previous paper
Dordevic 2015 [79]	ANN	accuracy	Noise parameter modelling
Abubakr 2018 [83]	ANN , SVM, DT	MSE	Modelling of I-V characteristics
Marinkovic 2014[78]	ANN	MAG and MSG Percentage	temperature-dependent S-parameter modeling
Jarndal 2019 [91]	ANN-GA, PSO, GWO	error rate	Combines ANN with different optimization techniques.
Husain 2023[80].	ANN	Execution time	Testing ANN on different software environments MATLAB, Python, and R
Marinkovic 2019[26]	ANN	Percentage error	S-parameter modelling over several types of FET
Geng 2021[86]	SVR	Accuracy	S-parameter error correction model
Geng 2020[85]	SVR	Accuracy, percentage error	S-parameter modelling
Jarndal 2020[92]	GA	MSE , accuracy	S-parameter modelling
Jarndal 2021[87]	ANN, SVR, PSO	MSE	S-parameter modelling
Hussein 2017 [69]	GA, PSO, ABC	Percentage error	Parameter extraction and extrinsic parameter tuning and S-parameter simulation
jarandal 2019 [67]	ANN-GA	Validatedwith measuredvalue graphically	Electrothermal modeling and Large signal model
Khusro 2018 [82]	SVR		S-parameter modelling
Khusro 2019[89]	ANN, SVR, DT	MSE	S-parameter modelling
Khusro 2019[27]	NARX based ANN	MSE	S-parameter modeling
Khusro 2019[84]	Analyticaland SVR	MSE,co-relation coefficient	Parameter extraction and S-parameter modelling
Khusro 2020[29]	MLP and Cascade structure	accuracy, convergence rate and generalization capability	Small signal modelling
Khusro 2020[32]	PSO- SVR	accuracy	small signal behavioral modeling
Husain 2021 [93]	GPR	MSE	small signal modeling
Husain 2021[36]	Distinct ANN architectures	MSE, MAE, fitting curves, and R2	small signal behavioral modelling
Mishra 2022[31]	Random Forest	MAE , MSE	A cross-platform application predicts GaN HEMT device scattering (S-) parameter,gain, power, device width, and traps.
Husain 2022 [30]	SVR,Gaussian Process Regression, DT, GA ANN, RANdom SAmple Consensus, AdaBoost, XGBoost	MSE, MAE, and R2	S-parameter small signal modeling
Husain 2023 [94]	Marine Predators Algorithm (MPA), Pelican Optimization Algorithm (POA) and Tunicate Swarm Algorithm (TSA)	execution time	small signal parameter extraction and optimization
Ahmad 2024[95]	MLP-ANN, DT, RF	MAE, MSE, RMSE, R2	S-parameter modelling
Ahmad 2024[96]	linear regressions and regularization, DT, RF, GBR, SVR	MAE, MSE, RMSE, R2	S-parameter modelling

MSE, RMSE, is a more interpretable measure of prediction errors. It penalizes larger errors more heavily than MAE, making it sensitive to outliers.

- Percentage error: Percentage error is a metric used to express the error or the difference between an estimated or predicted value and the actual or observed value as a percentage of the actual value. It is often used in prediction tasks to quantify the accuracy of predictions. The formula for percentage error is:

Table 5 — Limitations unique to each ML model

ML Model	Limitation
Linear Regression	Inability to capture nonlinearity, making it too simplistic for GaN HEMT modeling; susceptibility to outliers, leading to skewed predictions in high-frequency or high-power regions.
Decision Trees	Overfitting tendencies especially when they grow too deep or when the dataset is noisy Deep decision trees can memorize the training data, leading to poor generalization on unseen data
Support Vector Machines (SVM)	High computational cost for large datasets, limiting scalability; sensitivity to kernel choice, requiring time-consuming optimization.
Artificial Neural Networks (ANN)	High data requirements, risking overfitting with limited data; black-box nature, reducing interpretability for engineers.
Random Forests	Computational inefficiency due to multiple trees, impacting real-time applicability; difficulty capturing extreme nonlinearities in GaN HEMT behavior
Gradient Boosting Machines (GBM)	Susceptibility to overfitting with noisy or small datasets; high computational demand and slow training time.
Gaussian Process Regression (GPR)	Scalability issues due to O(n3)O(n^3)O(n3) complexity, limiting use with large datasets; assumption of stationarity, struggling with non-stationary data patterns.
K-Nearest Neighbors (KNN)	Curse of dimensionality, leading to degraded accuracy with high-dimensional data; sensitivity to distance metric, making it challenging to capture complex GaN HEMT behaviors.
Genetic Algorithm (GA)	Computationally expensive due to iterative population-based approach, especially for large datasets; tendency to converge prematurely to suboptimal solutions without proper diversity maintenance.
Particle Swarm Optimization (PSO)	Susceptible to stagnation, where particles cluster around a local optimum without further improvement; difficulty balancing exploration and exploitation, potentially missing global optima.

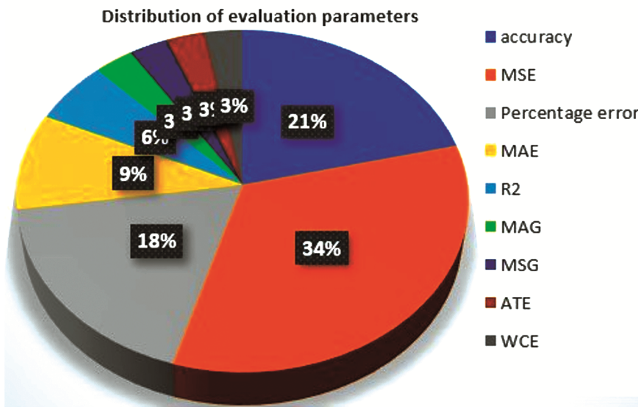

Fig 16 — Distribution of ML approaches used

Percentage error $E_{ij}[\%] =$

$$\frac{1}{N_f}\sum 100\left|\frac{S_{ij\,\text{Meas}}(f)-S_{ij\,\text{Simul}}(f)}{S_{ij\,\text{Meas}}(f)}\right| \quad \ldots (5)$$

- Worst-case error: The worst-case error represents the maximum or largest error that a model or system can encounter under specific conditions or scenarios. It helps in understanding the upper limit of error or the most challenging situation for a model's performance. This concept is often used in worst-case analysis and can be important for safety-critical systems.
- ATE: The average test error provides an overall assessment of how well the model performs on unseen data. Lower values of average test error indicate that the model generalizes well and is making accurate predictions on new, previously unseen examples. In contrast, higher average test error suggests that the model may not generalize effectively, and there might be issues like overfitting or underfitting.
- Mean relative error: Mean relative error is a measure of prediction accuracy that calculates the average relative difference between predicted values and actual values. It is expressed as a percentage and is useful for assessing the average prediction quality of a model across a dataset. The formula for mean relative error is similar to percentage error but applied to a set of predictions:
- Residual error: Residual error, often referred to as the residuals, is the difference between the observed or actual values and the predicted values in a regression analysis. It represents how far off the model's predictions are from the actual data points. Residuals are used to assess the goodness of fit of a regression model. Smaller residuals indicate a better fit.
- R-squared (R2 or Coefficient of Determination): Indicates the proportion of the target variable's variance that the model explains. The range of values is from 0 to 1, with higher values indicating a better fit. Through the literature review, we can

say that researchers evaluated their models using different evaluation metrics and validation approaches. Fig. 16 presents the distribution of the top most frequently used evaluation metrics based on our paper pool. Mean Squared Error (MSE) and R-squared (R^2) are the most commonly used metrics in regression analysis due to their simplicity, interpretability, and widespread acceptance. MSE emphasizes larger errors by averaging the squares of the discrepancies, making it effective for detecting outliers while providing a straightforward measure of overall prediction error. Its monotonic relationship with RMSE ensures flexibility in usage, and its acceptance in the literature standardizes it as a benchmark for comparison. R^2 complements MSE by quantifying the proportion of variance in the dependent variable explained by the model, offering an intuitive performance metric bounded between 0 and 1, with 1 indicating a perfect fit. Together, these metrics provide a robust framework for evaluating regression models, balancing error quantification with interpretability and generalizability.

7 Challenges in Machine Learning-Based Modeling

Getting enough high-quality data for machine learning, especially in specialized areas like semiconductor modeling, can be tough. Real-world data often come with noise and missing values, which need careful cleaning to ensure good model performance. Many ML models are like “black boxes,” making it hard to understand how they arrive at their predictions, which is a problem when you need to know the underlying reasons. Training complex models is resource-intensive and can be expensive, and scaling them for large datasets or real-time use is challenging. Models can also overfit, meaning they work well on training data but struggle with new, unseen data. Properly validating models is crucial but can be complicated. Additionally, ML models might pick up biases from the data they’re trained on, leading to unfair or inaccurate predictions, and they can be vulnerable to attacks that trick them into making errors, raising concerns about their security and reliability. Conventional Artificial Neural Networks (ANNs) face several drawbacks, including having a fixed number of neurons and activation functions, which limits their flexibility. They are highly sensitive to initial weights and often require careful initialization. Training with gradient-based methods can be slow and may suffer from getting stuck in local minima, leading to suboptimal solutions. Additionally, methods like Bayesian optimization can have slow convergence rates. On the other hand, Genetic Algorithms (GAs) offer fast convergence but are prone to getting trapped in local optima, potentially preventing them from finding the best solution. Also, Parameters like DC bias points, S-parameters, and small signal gain are typically consistent with real measurements in GaN HEMT modeling. However, non-linear behaviors, parasitic effects, and temperature or aging variations should be treated with caution, as they are more sensitive to operating conditions and harder to predict. Accurate modeling requires careful consideration of these factors.

7.1 Strategies to address data limitations

Synthetic data generation using physics-based TCAD simulations can fill gaps in experimental data, particularly under scarce operational conditions. Transfer learning enables the adaptation of models trained on related devices, reducing dependency on extensive HEMT-specific datasets. Fine-tuning pre-trained models with limited HEMT data further enhances their applicability. Active learning, with a focus on uncertain regions, facilitates targeted and iterative data collection, optimizing resource efficiency. Hybrid modeling, integrating ML with physics-based approaches, improves accuracy and data efficiency by leveraging domain knowledge. Additionally, methods such as missing value imputation, noise reduction with autoencoders, and k-fold cross-validation maximize the utility of available data, ensuring robust model performance despite limitations in data quality and quantity.

Additional recurring challenge we came across and which could be a topic for future research Traditional ML models are static they do not inherently adapt to changing device conditions (eg, temperature), input parameters (geometry of the device) and device layer structure(change in substrate layer of device or cap layer or introduction of field plate). If we specifically talk about GaN HEMTs, there are many structures of GaN HEMT (eg., AlGaN/GaN HEMT, AlGaN/InGaN/GaN HEMT, InAlN/GaN HEMT, AlN/GaN HEMT, GaN/InGaN/GaN HEMT) and are constant researches are being done and new structures are proposed for meeting the desired application and result. ML model trained on one specific GaN HEMT structure may not generalize accurately or efficiently

to other device designs. Each new structure, with its unique characteristics and operating conditions, would likely necessitate retraining or training from scratch to achieve reliable performance. This static nature of traditional ML models underscores the need for more adaptive and generalizable approaches that can handle the evolving nature of GaN HEMT technology without requiring extensive rework for each new design.

8 Conclusion

This work provides a comprehensive analysis of behavioral modeling for GaN HEMTs by comparing various methods for small-signal modeling. It examines key HEMT characteristics, including scattering parameters, bias points, temperature effects, geometrical dimensions, and electrical properties, aiming to enhance the understanding and development of accurate models. There is no universal best modeling approach; the suitability of a method depends on the specific constraints and requirements of the application in the context of GaN HEMT modeling, various machine learning techniques are evaluated based on key factors such as prediction accuracy: Techniques that minimize prediction error in metrics such as MAE, RMSE *etc*, the ability to capture the complex nonlinear device physics: ML techniques such as Support Vector Machines (SVM), Neural Networks (NN), or Ensemble models, are often prioritized, the simpler models like linear regression were unable to capture the complexities and were least efficient. Data availability is one of the major factors for selection criteria for ML technique as data for ML training be limited or costly to obtain for GaN HEMTs so we need to choose the technique that can perform on low datasets like SVM rather than data-hungry techniques like deep neural network. Generalization capability is one of the vital selection criteria for the chosen ML technique as the model needs to generalize across a wide range of operational conditions and be robust. The review highlights the limitations of conventional HEMT modeling approaches and underscores the necessity of exploring alternative methods. The paper extensively surveys and critically evaluates machine learning (ML)-based approaches for small-signal GaN HEMT modeling. It covers ML techniques such as Artificial Neural Networks (ANNs), Support Vector Regression (SVR), Decision Trees (DT), Particle Swarm Optimization (PSO), and Genetic Algorithms (GAs), discussing their precision, complexity, and computational efficiency. Notable regression and optimization techniques are presented, illustrating their application in HEMT modeling. Challenges associated with ML modeling are addressed, emphasizing the need for further exploration in this rapidly evolving field. This study serves as a valuable resource for electrical and semiconductor device engineers and researchers by providing insights into various HEMT modeling methodologies, identifying knowledge gaps, and encouraging future research and collaboration. The paper aids researchers in selecting appropriate models for HEMT design, optimization, and performance enhancement, detailing the advantages, limitations, and applications of each method.

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