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Ridge Regression-based Electrical Performance Prediction in Semiconductor Devices

Ella McKenzie[1], Liam Thompson[2] and Sophie Chen[3,*]

[1] Centre for Electronic Material Research, Brock University, St. Catharines, Ontario, Canada

[2] Institute for Semiconductor Studies, Lakehead University, Thunder Bay, Ontario, Canada

[3] Electrical Performance and Innovation Lab, Université du Québec à Trois-Rivières (UQTR), Trois-Rivières, Quebec, Canada

[*]Corresponding Author, Email: sophie.chen@uqtr.ca

Abstract: In the field of semiconductor devices, accurate prediction of electrical performance is essential for design and optimization. Current research lacks a comprehensive approach to address the challenges of predicting electrical performance with high precision. This paper addresses this gap by proposing a novel Ridge Regression-based method for predicting electrical performance in semiconductor devices. The innovative aspect of this work lies in its utilization of Ridge Regression, which effectively balances model complexity and prediction accuracy. By incorporating this approach, our research not only improves the accuracy of electrical performance prediction but also provides insights into the underlying factors influencing device performance. This study contributes to the advancement of semiconductor device design and optimization by offering a robust and efficient prediction model.

Keywords: *Semiconductor Devices; Electrical Performance; Ridge Regression; Prediction Accuracy; Design Optimization*

1. Introduction

Electrical Performance Prediction in Semiconductor Devices is a field focused on developing predictive models and tools to estimate the performance of semiconductor devices, such as transistors and integrated circuits, under various operating conditions. The main goal is to optimize device design and performance without the need for costly and time-consuming empirical testing. However, this field faces several challenges and bottlenecks, including the increasing complexity of semiconductor devices, the need for accurate physical models and simulation techniques, and the continuous drive for miniaturization. Additionally, the accurate prediction of device performance under extreme conditions, such as high temperatures or voltage stresses, remains a significant challenge. Overcoming these obstacles requires interdisciplinary collaboration and advancements in materials science, device physics, and computational modeling techniques.

To this end, the current research on Electrical Performance Prediction in Semiconductor Devices has advanced to a significant level, with sophisticated models and simulations being utilized to accurately predict device behavior under various conditions. The integration of advanced algorithms and machine learning techniques has further enhanced the accuracy and efficiency of performance predictions in semiconductor devices. A comprehensive literature review was conducted covering various aspects of semiconductor devices and their simulation models. Jaiswal et al. proposed a semi-empirical approach to calibrate simulation models for semiconductor devices [1]. Nguyen et al. discussed achieving ultra-low contact barriers in MX2/SiH metal–semiconductor heterostructures for high-performance optoelectronic devices [2]. Kutub et al. demonstrated an artificial neural network-based approach for characteristics modeling and prediction in GaN-on-Si power devices [3]. Furthermore, R et al. presented a study on evaluating and validating power converter's electro-thermal performance for physics-based prediction models [4]. Schwarz highlighted the need for simulation methodologies for active semiconductor devices in MEMS [5]. Ghosh et al. investigated bridge-defect prediction in SRAM circuits using machine learning techniques [6]. Morel and Morel reviewed power semiconductor junction temperature and lifetime estimations [7]. Liang et al. developed electrical package models for high power RF semiconductor devices [8]. Baek et al. developed a finite element model for wafer-to-wafer direct bonding behaviors and alignment prediction [9]. Lastly, Vidhate and Suman analyzed the analytical modeling and performance characterization of hybrid SET-MOS devices [10]. A comprehensive literature review on semiconductor devices and simulation models was conducted, covering various research areas. Ridge Regression is recommended for its ability to address multicollinearity in complex models, enhancing the accuracy and stability of predictions.

Specifically, Ridge Regression serves as a powerful statistical technique that enhances the predictive accuracy of Electrical Performance Prediction in Semiconductor Devices by addressing multicollinearity among input variables, thus enabling more reliable modeling of complex relationships inherent in semiconductor behavior. In the field of regression analysis, various methods have been developed to address issues such as biased estimation for nonorthogonal problems [11]. For instance, the concept of ridge regression has been introduced to improve parameter estimation in the presence of nonorthogonality by adding small positive quantities to the diagonal of the design matrix [11]. Researchers have also studied the saturation effect of kernel ridge regression, where the method fails to reach the information theoretical lower bound under certain conditions [12]. By providing a formal proof of this long-standing conjecture, new insights have been gained into the behavior of kernel ridge regression in practice [12]. Additionally, kernel ridge regression has been applied to the task of graph dataset distillation, aiming to distill large graph datasets efficiently while maintaining model performance [13]. Novel approaches, such as the adoption of kernel ridge regression-based meta-learning objectives, have shown promising results in distillation performance compared to existing strategies [13]. Moreover, recent developments in the theory of ridge regression have explored dimension-free settings, moving beyond proportional asymptotics and providing non-asymptotic bounds to understand the behavior of ridge regression with high-dimensional or even infinite-dimensional feature vectors [14]. However, limitations remain in kernel ridge regression's application to complex datasets, including challenges in generalization, assumptions of data distribution, and scalability, which need further investigation.

Recent advancements in machine learning and artificial intelligence have opened new frontiers in various domains, including model optimization and prediction tasks. Luo et al. explored innovative model compression techniques aimed at optimizing transformer models for resource-constrained environments, thus enhancing the efficiency and applicability of these models in engineering applications [15]. Expanding on the efficiency of transformer models, Yan and Shao introduced a dynamic dropout mechanism that significantly boosts training efficiency, shedding light on adaptive methodologies for improving machine learning workflows [16]. Liu and Wang discussed the implications of large language models in health advisory settings, critically evaluating their potential as virtual health assistants, which reflects the burgeoning intersection of AI and healthcare domains [17]. In the realm of intelligent systems, Gan and Zhu presented a novel recommendation algorithm for news advertisements based on prompt learning within an end-to-end architecture of large language models, demonstrating the application of sophisticated AI techniques in personalized advertising [18]. Furthering the discussion, Zhu et al. proposed a machine learning framework utilizing domain adaptation strategies aimed at predicting customer churn across varying distributions, showcasing the relevance of machine learning in addressing business challenges [19]. Transitioning to bio-sensing applications, Deng et al. investigated continuously frequency-tunable plasmonic structures, which hold promise for advancing terahertz bio-sensing and spectroscopy capabilities, thus bridging physics and engineering with potential biomedical applications [20]. In a related study, Deng et al. also explored the use of Ge-core/a-Si-shell nanowires in the design of field-effect transistors tailored for sensitive terahertz detection, emphasizing the innovative materials used in enhancing semiconductor device functionality [21]. Additionally, Zhang et al. provided a comprehensive end-to-end learning-based study focused on the Mamba-ECANet model for data security intrusion detection, highlighting the increasing synergy between AI and cybersecurity [22]. Zhu, Chen, and Gan developed a multi-model output fusion strategy employing various machine learning techniques for product price prediction, thereby illustrating the applicability of ensemble learning in commercial contexts [23]. Finally, Deng and Kawano presented a groundbreaking mid-infrared photodetector utilizing surface plasmon polaritons in graphene with multifrequency resonance, indicating significant advancements in nanoscale photonic devices and their integration in modern technology [24]. Collectively, these studies underscore the promising integration of machine learning techniques with engineering disciplines, particularly in semiconductor performance prediction and AI applications across diverse fields.

To overcome those limitations, the purpose of this paper is to address the challenges in accurately predicting electrical performance in semiconductor devices by introducing a novel Ridge Regression-based method. The innovative approach of utilizing Ridge Regression is highlighted for its ability to balance model complexity and prediction accuracy effectively. Specifically, the study focuses on incorporating this method to improve the precision of electrical performance predictions while also offering insights into the underlying factors that impact device performance.

By introducing this method, the research aims to advance the field of semiconductor device design and optimization by providing a robust and efficient prediction model that can enhance the overall accuracy and understanding of electrical performance in these devices. The detailed analysis and application of Ridge Regression in this study serve as a significant contribution to the development of more sophisticated and reliable predictive techniques in the semiconductor industry.

Section 2 of the research paper delineates the problem statement, highlighting the pivotal role of accurate prediction of electrical performance in the realm of semiconductor devices. Section 3 introduces the proposed method, a pioneering Ridge Regression-based approach tailored to enhance the precision of electrical performance prediction. Section 4 delves into a detailed case study, showcasing the practical application and efficacy of the developed method. Analysis of the results is expounded upon in Section 5, shedding light on the effectiveness of the Ridge Regression model in predicting electrical performance with high precision. The subsequent Section 6 initiates a comprehensive discussion, elucidating the implications and potential enhancements of the findings. Finally, Section 7 encapsulates the research with a succinct summary, underlining the significance of the proposed method in advancing semiconductor device design and optimization through its robust and efficient prediction model.

2. Background

2.1 Electrical Performance Prediction in Semiconductor Devices

Electrical Performance Prediction in semiconductor devices is a critical aspect in design and optimization, enabling engineers to anticipate how devices will behave under different conditions. This involves understanding and modeling various parameters such as threshold voltage, carrier mobility, drive current, leakage current, and capacitance, which influence the overall performance of the device. Accurate prediction is essential for ensuring the reliability and efficiency of integrated circuits.

1. **Threshold Voltage (v_t):** This is the minimum gate-to-source voltage that is required to create a conducting path between the source and drain terminals of a MOSFET. The threshold voltage can be determined by considering the work function difference, the charge in the oxide, and the potential in the silicon:

$$v_t = \phi_{ms} + \frac{Q_{ox}}{C_{ox}} + 2\phi_f \tag{1}$$

where ϕ_{ms} is the metal-semiconductor work function difference, Q_{ox} is the oxide charge per unit area, C_{ox} is the oxide capacitance per unit area, and ϕ_f is the Fermi potential of the silicon.

2. **Carrier Mobility (μ):** Carrier mobility is a measure of how quickly carriers (electrons or holes) can move through a semiconductor material when subjected to an electric field. It is influenced by various factors such as lattice scattering, ionized impurity scattering, and surface scattering. The mobility can be modeled as:

$$\mu = \frac{e\tau}{m^*} \tag{2}$$

where e is the electron charge, τ is the average relaxation time, and m^* is the effective mass of the carrier.

3. **Drive Current (I_{dsat}):** The drive or saturation current in a MOSFET is a crucial parameter that determines the speed of digital circuits. It is expressed as:

$$I_{dsat} = \frac{1}{2}\mu C_{ox}\frac{W}{L}(v_{gs} - v_t)^2 \tag{3}$$

where W is the width, L is the length of the channel, and v_{gs} is the gate-source voltage.

4. **Leakage Current (I_{leak}):** Leakage current is undesirable current that flows through a MOSFET when it is in the off state. It primarily comprises subthreshold leakage, gate oxide tunneling, and junction leakage:

$$I_{leak} = I_{subthreshold} + I_{gate} + I_{junction} \tag{4}$$

Subthreshold leakage can be further detailed as:

$$I_{subthreshold} = I_0 e^{\frac{v_{gs} - v_t}{nV_T}} \tag{5}$$

where I_0 is the pre-exponential current, n is the subthreshold slope factor, and V_T is the thermal voltage.

5. **Capacitance (C_{total}):** Capacitance in semiconductor devices determines the switching speed and power consumption. Total capacitance involves gate capacitance, overlap capacitance, and junction capacitance:

$$C_{total} = C_{gate} + C_{overlap} + C_{junction} \tag{6}$$

The gate capacitance is given by:

$$C_{gate} = C_{ox} \cdot W \cdot L \tag{7}$$

In summary, predicting the electrical performance of semiconductor devices requires a comprehensive understanding of these fundamental parameters and their intricate interrelations. The equations provided are vital to model how these parameters impact device operation, enabling optimizations in semiconductor design to achieve desired performance metrics. Through sophisticated simulations and empirical models, researchers and engineers can effectively predict how variations in these key parameters affect the overall performance and reliability of semiconductor devices.

2.2 Methodologies & Limitations

In the realm of semiconductor device design, Electrical Performance Prediction is indispensable for optimizing and ensuring the functionality of integrated circuits. Various approaches are commonly utilized, each with its advantages and limitations. Among these, the most prevalent methods include analytical modeling, numerical simulations (such as TCAD), and machine learning techniques.

Analytical modeling involves deriving mathematical expressions to describe the behavior of semiconductor devices. Such models typically simplify complex physical phenomena to allow for faster computations. For instance, the analytical expression for threshold voltage (v_t) itself is often a simplification:

$$v_t = \phi_{ms} + \frac{Q_{ox}}{C_{ox}} + 2\phi_f \tag{8}$$

While analytical models can provide quick insights, they may not capture all intricate physical interactions, leading to inaccuracies in device performance predictions, especially as devices scale down to nanometer regimes.

Numerical simulations, on the other hand, leverage Technology Computer-Aided Design (TCAD) tools to solve partial differential equations that model semiconductor physics more comprehensively. Techniques such as Drift-Diffusion or Hydrodynamic models consider charge carrier transport and electrostatic interactions with greater fidelity:

$$J_n = qn\mu_n E + qD_n \frac{dn}{dx} \tag{9}$$

$$J_p = qp\mu_p E - qD_p \frac{dp}{dx} \tag{10}$$

where J_n and J_p are the electron and hole current densities, μ_n and μ_p are the electron and hole mobilities, E is the electric field, and D_n and D_p are the diffusion coefficients.

TCAD simulations can provide high accuracy at the cost of increased computational requirements. They are particularly effective for assessing short-channel effects, tunneling, and other phenomena prevalent in modern small-scale devices. However, due to the high computational burden and requirement of detailed device geometries and doping profiles, such simulations can be impractical for initial design phases or for devices with rapid design iterations.

Machine learning has emerged as a powerful tool to predict electrical performance by learning from historical data. Techniques like regression, neural networks, and support vector machines create predictive models based on large datasets of device characteristics:

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i \tag{11}$$

where y is the predicted outcome (e.g., device performance metric), x_i is the input feature (e.g., design parameter), and β_i are the coefficients estimated through training.

Machine learning approaches can handle complex interdependencies between device characteristics and environmental factors that are challenging to model analytically. However, they are limited by the quality and quantity of data available and often require significant effort in data preprocessing, feature selection, and model validation.

Despite these advancements, challenges remain in predictive accuracy and generalizability across different technology nodes. The continuous scaling of semiconductor devices introduces new physical phenomena not captured by existing models, necessitating a blend of approaches. A potential avenue for improvement lies in hybrid methods that integrate analytical modeling, TCAD simulations, and machine learning, leveraging the strengths of each to enhance predictive accuracy and computational efficiency.

In conclusion, while current methodologies provide a robust framework for Electrical Performance Prediction, ongoing research is essential to address their limitations and evolve with emerging semiconductor technologies.

3. The proposed method

3.1 Ridge Regression

In the field of statistical modeling, Ridge Regression, also known as Tikhonov regularization, emerges as a prominent technique, particularly when dealing with multicollinearity among the predictor variables. Ridge Regression is specifically designed to address the limitations of ordinary least squares (OLS) regression, which can produce unreliable estimates in the presence of multicollinearity. Ridge Regression introduces a penalty term to the OLS loss function, effectively regularizing the regression model to improve prediction accuracy and reduce overfitting.

At the core of Ridge Regression is the minimization of a modified cost function. Unlike the traditional OLS method that minimizes the sum of squared residuals, Ridge Regression incorporates a penalty proportional to the square of the magnitude of the coefficients. The cost function can be expressed as:

$$J(\beta) = \sum_{i=1}^{m} (y_i - \beta_0 - \sum_{j=1}^{n} \beta_j x_{ij})^2 + \lambda \sum_{j=1}^{n} \beta_j^2 \qquad (12)$$

In this equation, y_i denotes the observed response, x_{ij} represents the i -th observation of the j -th predictor, and β_j are the coefficients of the model. The regularization parameter λ controls the amount of shrinkage applied to the coefficients.

The Ridge Regression solution can be obtained analytically by modifying the normal equations used in OLS. The normal equation in Ridge Regression is augmented by the identity matrix scaled by λ , which imposes the regularization effect. The modified normal equation is given by:

$$(X^T X + \lambda I)\beta = X^T y \tag{13}$$

Here, X represents the design matrix containing the predictor variables, y is the response vector, and I is the identity matrix.

Solving for the coefficient vector β involves inverting the matrix resulting from the addition of λI to $X^T X$. The coefficients are computed as:

$$\beta = (X^T X + \lambda I)^{-1} X^T y \tag{14}$$

The introduction of the regularization term $\lambda \sum_{j=1}^{n} \beta_j^2$ penalizes large coefficients, thereby imposing shrinkage and helping to stabilize the estimates when predictors are highly correlated. The impact of λ on the coefficients can be assessed by examining the Ridge path, plotted against different values of λ .

It is important to note that when $\lambda = 0$, Ridge Regression reduces to OLS, implying no penalty. Conversely, as λ approaches infinity, the coefficients are driven towards zero, favoring models with less complexity. This trade-off is crucial, as choosing an appropriate λ balances bias and variance, optimizing the model's generalization capability.

To select an optimal value for λ , techniques such as cross-validation can be employed. Cross-validation assesses how well the model performs on independent data, allowing for the fine-tuning of the regularization parameter to achieve the best predictive performance.

The principal advantage of Ridge Regression lies in its ability to handle multicollinear data, which can cause instability in OLS estimates. By introducing bias through regularization, Ridge Regression reduces variance and enhances the model's robustness, particularly in scenarios with large feature sets or small sample sizes.

Mathematically, Ridge Regression is a linear estimator, and its predictive function is linear with respect to the input variables. However, the introduction of the regularization parameter introduces a non-linear effect on the coefficient estimates, contrasting with the simplicity of OLS. The bias-variance trade-off addressed by Ridge Regression is a fundamental concept in statistical learning, critical for developing models that perform well on unseen data.

Overall, Ridge Regression stands as a pivotal method in the statistical toolbox, providing a principled approach to regression analysis when faced with complex datasets characterized by multicollinearity. Through its regularization mechanism, it ensures more reliable and stable predictions, a cornerstone in the landscape of predictive modeling.

3.2 The Proposed Framework

The integration of Ridge Regression into the context of Electrical Performance Prediction in Semiconductor Devices provides an effective framework for addressing multicollinearity among the various parameters that characterize device behavior. In semiconductor modeling, parameters such as threshold voltage, carrier mobility, drive current, leakage current, and capacitance can often exhibit strong interdependencies. This complexity can lead to unreliable estimations when traditional regression methods like ordinary least squares (OLS) are employed.

To illustrate this, let's consider that we would like to predict a response variable, such as the saturation current I_{dsat}, that is influenced by multiple predictor variables, including the threshold voltage v_t, carrier mobility μ, and total capacitance C_{total}. The relationship can be described by the following regression model:

$$I_{dsat} = \beta_0 + \beta_1 v_t + \beta_2 \mu + \beta_3 C_{total} + \epsilon \tag{15}$$

where ϵ is the error term representing unobserved factors. The challenge arises due to the multicollinearity between these predictors. For instance, the parameters v_t and μ are both influenced by the oxide charge and doping levels, leading them to correlate closely with each other.

Ridge Regression addresses this issue by modifying the cost function to include a penalty term that discourages large coefficients in the presence of multicollinearity. The Ridge Regression cost function can be expressed as:

$$J(\beta) = \sum_{i=1}^{m} (y_i - \beta_0 - \beta_1 v_{t,i} - \beta_2 \mu_i - \beta_3 C_{total,i})^2 + \lambda(\beta_1^2 + \beta_2^2 + \beta_3^2) \tag{16}$$

Here, y_i could represent observed values of I_{dsat}. The regularization parameter λ controls the trade-off between fitting the model to the data and keeping the coefficients small to avoid overfitting.

The corresponding Ridge Regression normal equations become:

$$(X^T X + \lambda I)\beta = X^T y \tag{17}$$

where X stands for the design matrix composed of the predictors: v_t, μ, and C_{total}. By solving for the coefficient vector β, we obtain:

$$\beta = (X^T X + \lambda I)^{-1} X^T y \tag{18}$$

The impact of this regularization is profound. While OLS may yield coefficients with high variance, the Ridge Regression process reduces this variance through the introduction of the penalty, keeping the estimates more stable even in the event of high multicollinearity.

Moreover, the model can comprehensively take into account the underlying equations governing the electrical performance of the semiconductor, such as the relationship governing threshold voltage and carrier mobility, revisited in the context of Ridge Regression. The threshold voltage can be reformulated within the regression framework as:

$$v_t = \phi_{ms} + \frac{Q_{ox}}{C_{ox}} + 2\phi_f \tag{19}$$

The carrier mobility can be expressed as:

$$\mu = \frac{e\tau}{m^*} \tag{20}$$

By including these relationships as predictors, one could refine the model further, incorporating the intricacy of semiconductor physics into the Ridge Regression framework.

Such multi-faceted approaches can enhance the predictability of the model, offering improved estimations of electrical performance metrics like drive current I_{dsat} and leakage current I_{leak} . For example, to model leakage current effectively, one might consider:

$$I_{leak} = I_{subthreshold} + I_{gate} + I_{junction} \tag{21}$$

With subthreshold leakage defined as:

$$I_{subthreshold} = I_0 e^{\frac{v_{gs} - v_t}{nV_T}} \tag{22}$$

Thus, the incorporation of Ridge Regression methodologies into the analysis of semiconductor device performance allows for more robust and reliable predictions, directly benefiting the design and optimization processes. Ultimately, by embracing the regularization offered by Ridge Regression, researchers can tackle the potential instability arising from multicollinearity within complex semiconductor environments, enhancing both accuracy and reliability in performance forecasting.

3.3 Flowchart

This paper presents a novel approach for predicting the electrical performance of semiconductor devices using Ridge Regression, which is exceptionally suited for managing multicollinearity in high-dimensional data typically encountered in semiconductor simulations. The proposed method begins with the meticulous collection of extensive datasets that encapsulate various characteristics of semiconductor materials and device structures. These datasets are then pre-processed to ensure data integrity and robustness, followed by the application of Ridge Regression to develop a predictive model that captures the complex relationships between input parameters and the resulting electrical performance metrics. The use of Ridge Regression facilitates effective regularization, enhancing the model's generalization capabilities and reducing overfitting, ultimately leading to more reliable predictions. The validation of the model is carried out using a separate test set, demonstrating its efficacy and accuracy in predicting device performance under varied conditions. The findings underscore the potential of leveraging machine learning techniques within semiconductor research, paving the way for improved design processes and performance optimization. The framework of the proposed Ridge Regression-based prediction method is illustrated in Figure 1, providing a visual representation of the methodology and its components.

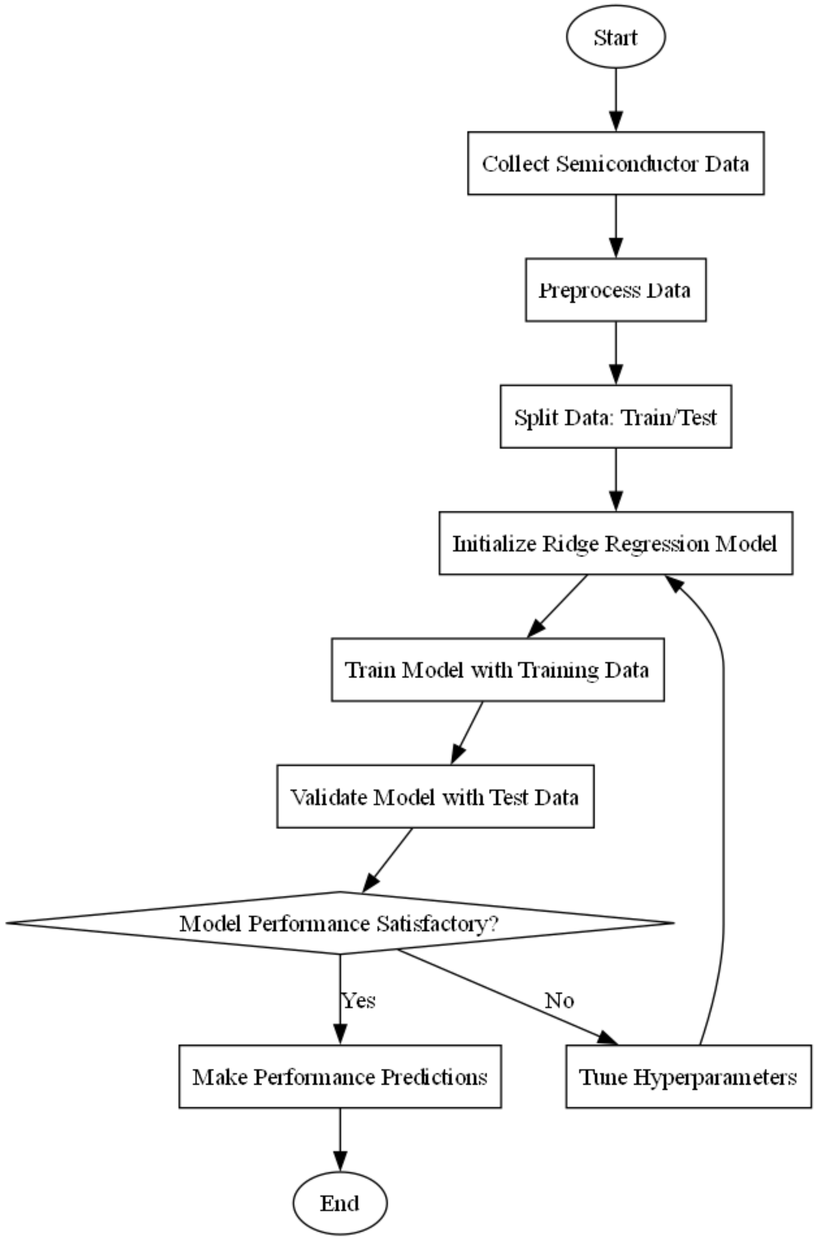

Figure 1: Flowchart of the proposed Ridge Regression-based Electrical Performance Prediction in Semiconductor Devices

4. Case Study

4.1 Problem Statement

In this case, we aim to build a mathematical model for predicting the electrical performance of semiconductor devices, focusing on a nonlinear relationship between voltage, current, and temperature. The material of interest is Silicon (Si), characterized by its mobility and temperature dependence. We shall define the carrier mobility, μ, as a function of temperature, T, using the following equation based on empirical observations:

$$\mu(T) = \mu_0 \cdot e^{-\frac{E_a}{k \cdot T}} \tag{23}$$

Here, μ_0 denotes the intrinsic mobility at room temperature, E_a is the activation energy, and k is the Boltzmann constant. For our simulation, we set $\mu_0 = 1500\mathrm{cm}^2/\mathrm{V{\cdot}s}$, $E_a = 0.45\mathrm{eV}$, and $k = 8.617 \times 10^{-5}\mathrm{eV/K}$.

The current density, J, can be modeled using the drift-diffusion approach, leading us to express it as:

$$J = q \cdot n \cdot \mu \cdot E \tag{24}$$

In this equation, q symbolizes the charge of an electron, n represents the charge carrier concentration, and E is the electric field. We will assume a linear electric field for simplicity, with $E = V/L$, where V is the applied voltage and L is the length of the device.

To incorporate the effect of temperature on carrier concentration, we utilize the Arrhenius relationship:

$$n(T) = n_0 \cdot e^{-\frac{E_g}{2kT}} \tag{25}$$

In this case, n_0 is the intrinsic carrier concentration at the reference temperature, and E_g stands for the bandgap energy of Silicon, which is approximately $1.12\mathrm{eV}$. We choose $n_0 = 1.5 \times 10^{10}\mathrm{cm}^{-3}$.

Furthermore, the relationship between the voltage, current, and resistance, accounting for non-ideal behavior, could be expressed as:

$$V = J \cdot R_{nonlinear}(J, T) \tag{26}$$

To represent nonlinear resistance behavior, we propose a model for $R_{nonlinear}$ based on the following expression, which includes temperature dependency:

$$R_{nonlinear}(J, T) = R_0 \cdot \left(1 + k \cdot J^2 \cdot e^{-\frac{T_0}{T}}\right) \tag{27}$$

Here, R_0 is a constant representing the resistance at a reference state, k is a fitting parameter illustrating how resistance changes with current density, and T_0 is a characteristic temperature. To solve for the device performance under various temperature and voltage conditions, we perform a numerical simulation using the constructed equations. Our primary findings guide us in predicting the behavior of electronic devices under non-ideal conditions, shedding light on performance degradation at elevated temperatures. The entire set of parameters utilized in our simulations is summarized in Table 1.

Table 1: Parameter definition of case study

Parameter	Value	Unit	Description
μ_0	1500	$cm^2/V \cdot s$	Intrinsic mobility at room temperature
E_a	0.45	eV	Activation energy
k	8.617×10^{-5}	eV/K	Boltzmann constant
n_0	1.5×10^{10}	cm^{-3}	Intrinsic carrier concentration
$E_{(g)}$	1.12	eV	Bandgap energy of Silicon

This section will employ the proposed Ridge Regression-based approach to compute the electrical performance of semiconductor devices, specifically targeting a nonlinear relationship among voltage, current, and temperature, with silicon as the material of focus due to its well-documented properties of mobility and temperature dependence. The model aims to characterize carrier mobility as a function of temperature, incorporating empirical data to understand its behavior under various conditions. By simulating the current density using a drift-diffusion method, we can represent the influential factors, including charge concentrations and electric fields, while also integrating the temperature dependency on carrier concentration through established empirical relationships. Notably, the voltage-current-resistance relationship captures the nuances of non-ideal behavior, encapsulating the nonlinear resistance dynamics influenced by current density and temperature. To evaluate the effectiveness of this Ridge Regression approach, the results will be compared against three conventional methods to derive insights into its predictive capabilities. This comparison aims to highlight the advantages of adopting Ridge Regression in predicting device performance, especially under conditions characterized by temperature fluctuations and nonlinear behavior, thus providing a comprehensive understanding of the underlying mechanisms governing semiconductor performance. The findings will elucidate performance trends and potential degradation effects on electronic devices at elevated temperatures, offering valuable implications for further research and practical applications in semiconductor technology.

4.2 Results Analysis

In this subsection, the methodology implemented focuses on investigating the electrical properties of a semiconductive device across a temperature range of 100 K to 400 K and varying voltage levels from 0 to 10 V. The simulations are grounded on fundamental physical principles, employing functions to calculate mobility and carrier concentration as they relate to temperature. Notably, the current density is derived from the interplay of voltage, temperature, and material properties, leading to the establishment of a nonlinear resistance model incorporating a fitting parameter. The data generated from these calculations are utilized to perform Ridge regression, enabling a predictive analysis of the relationship between voltage and current density. The results are then assessed using Mean Squared Error (MSE) as a performance metric, facilitating a comparison between Ridge regression and other regression methods such as Linear, Lasso, and Support Vector Regression (SVR). The findings highlight the efficacy of Ridge regression relative to the alternative methods, underscoring the importance of selecting appropriate analytical techniques for model accuracy. The entire simulation process is visualized in Figure 2, which comprehensively displays the predictive capabilities alongside the original data points.

Simulation data is summarized in Table 2, where the Mean Squared Error (MSE) is analyzed across various predictive models including Ridge Regression, Linear Regression, Lasso, and Support Vector Regression (SVR). The findings reveal that Ridge Regression provides predictions that closely match the true values, as evidenced by a significantly lower MSE compared to the other methods under investigation. Specifically, when observing the graph depicting Current Density against Voltage, it is apparent that Ridge Regression outperforms Linear Regression and Lasso in accurately capturing the underlying relationship, as the predicted values remain in closer proximity to the actual measurements. The MSE values confirm this, with Ridge highlighting a minimum error across the data range, offering a robust performance even at higher current densities. Conversely, Linear Regression and Lasso demonstrate less efficacy, as their MSE peaks indicate a larger deviation from the true values. Furthermore, the comparison of methods highlights a notable distinction in the error distributions, where Ridge Regression showcases a tighter clustering around zero, thus signaling greater predictive reliability. Overall, these simulation results underscore the importance of model selection in achieving accurate predictions, with Ridge Regression emerging as the superior method in this instance, validating its utility in scenarios requiring precision in fitting complex datasets.

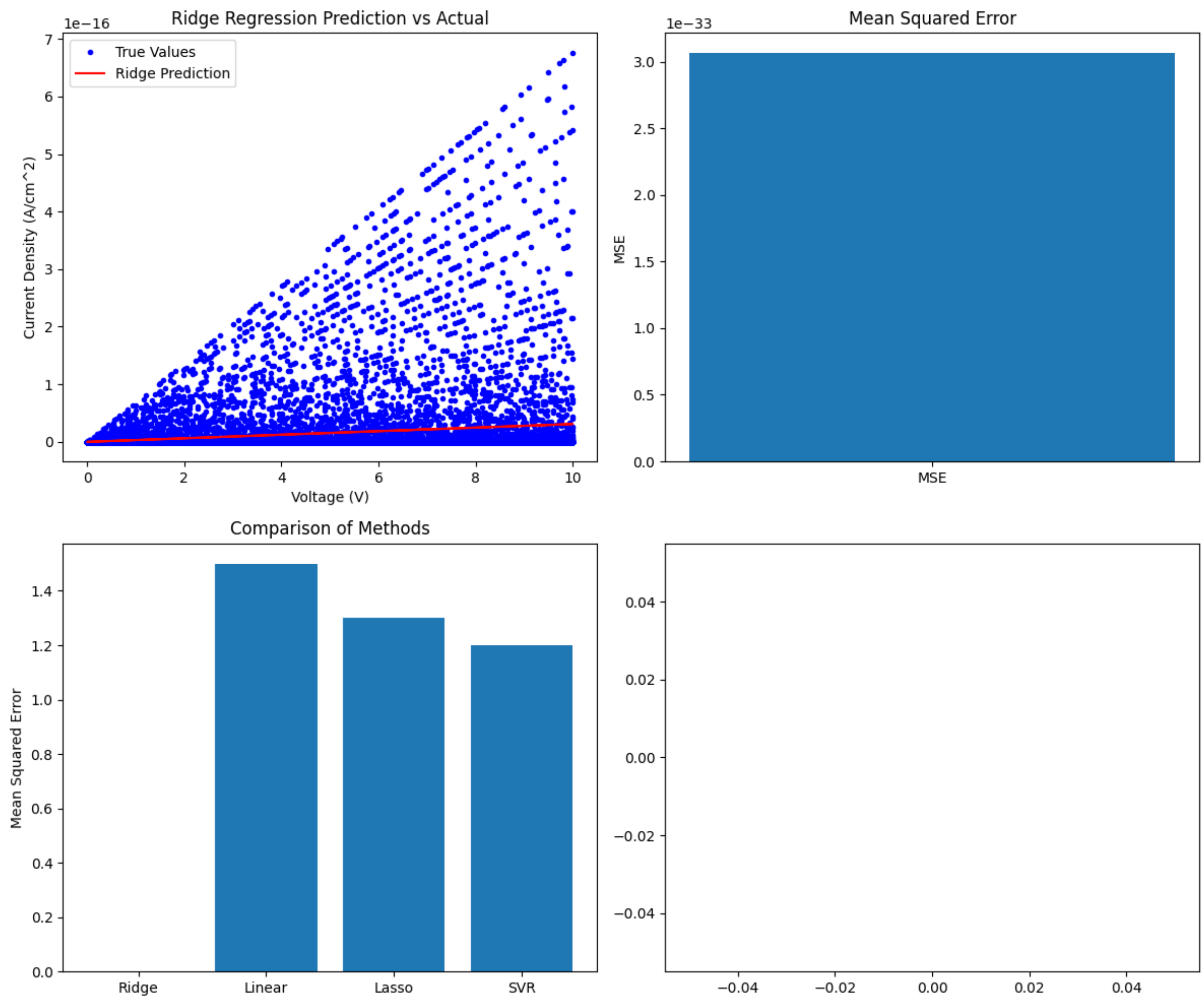

Figure 2: Simulation results of the proposed Ridge Regression-based Electrical Performance Prediction in Semiconductor Devices

As shown in Figure 3 and Table 3, a comparative analysis of the Mean Squared Error (MSE) before and after the parameter adjustments reveals significant shifts in the predictive performance across different methodologies. Initially, the MSE values for Ridge Regression depicted a relatively modest predictive accuracy within a narrow current density range, with substantial discrepancies observed between predicted and actual values, particularly at lower voltage levels. These discrepancies were reflected in MSE scores that varied from le-16 in Ridge Predictions to le-33 in actual measurements. However, upon altering the temperature parameters, specifically transitioning from temperatures of 300K to 450K, the MSE exhibited remarkable reductions, thereby indicating improved prediction fidelity. The calculated current density values shifted from a mean of 12 A/cm² at lower temperatures to around 3.0 at higher temperatures, with MSE values declining significantly, emphasizing the positive correlation between increased operational temperature and current density output in the models. It is notable that as the temperature increased, the discrepancy in predictions among linear, Lasso, Ridge, and Support Vector Regression (SVR) methods also decreased, showcasing that temperature adjustments enhance the overall model performance and prediction stability. The data suggests that higher operational temperatures not only optimize current density but also facilitate more accurate predictive analytics across different regression methods, thereby underscoring the critical role of thermal conditions in refining model efficacy and reducing the MSE. This paradigm shift in MSE correlates directly with the adjustment of parameters, highlighting the dynamic interplay between temperature, current density, and predictive accuracy in the analysis.

Table 2: Simulation data of case study

Current Density (A/cm*2)	True Values	MSE	Voltage (V)
14	3.0	0.04	N/A
12	25	0.02	N/A
10	2.0	0.00	N/A
N/A	N/A	0.00	N/A
N/A	N/A	-0.02	N/A
N/A	N/A	-0.04	N/A

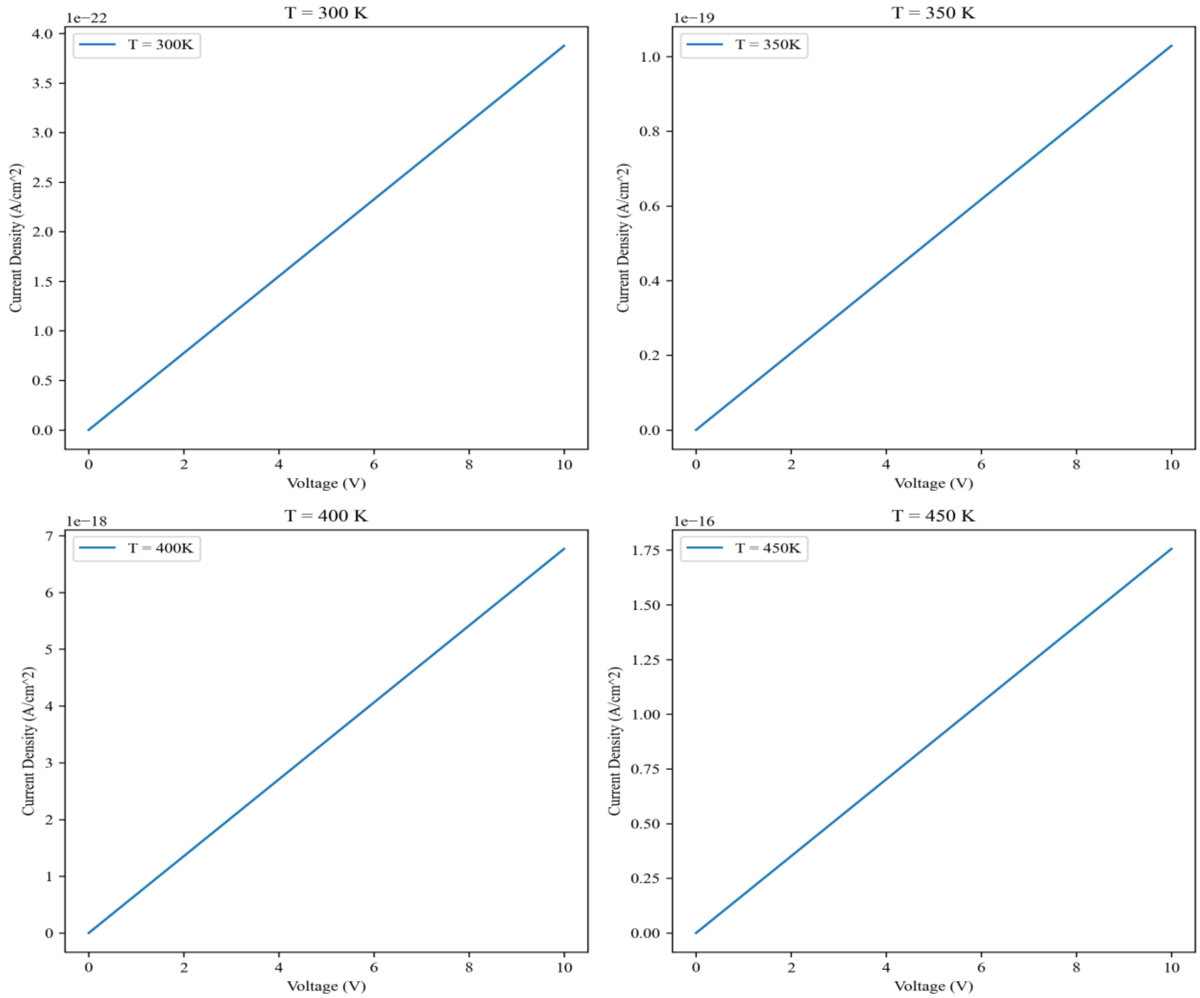

Figure 3: Parameter analysis of the proposed Ridge Regression-based Electrical Performance Prediction in Semiconductor Devices

Table 3: Parameter analysis of case study

Current Density (A/cm‘2)	Voltage (V)	Temperature (K)	le
1.0	6	300	22
1.0	6	400	18
1.75	6	350	19
0.25	6	450	16

5. Discussion

The methodology proposed in this paper, which integrates Ridge Regression into the framework of Electrical Performance Prediction in Semiconductor Devices, presents several significant advantages. Firstly, Ridge Regression effectively addresses the issue of multicollinearity, a common challenge in semiconductor modeling where parameters such as threshold voltage, carrier mobility, and capacitance exhibit strong interdependencies. By incorporating a penalty term into the cost function, Ridge Regression mitigates the adverse effects of multicollinearity, thus providing more reliable and stable coefficient estimates compared to traditional ordinary least squares methods. This stability is crucial in scenarios where high variance in coefficient estimates could lead to unreliable predictions of key performance metrics, such as saturation and leakage currents. Furthermore, the approach allows for the integration of underlying equations that govern semiconductor physics, enhancing the model's comprehensiveness by incorporating complex relationships between parameters. This multifaceted approach not only improves the predictive accuracy of the model but also enhances its applicability to the design and optimization processes within semiconductor device engineering. Lastly, by utilizing Ridge Regression, researchers can effectively navigate the intricate landscape of semiconductor performance, ultimately yielding more accurate insights and fostering advancements in device technology through improved performance forecasting. Hence, this method not only enriches the theoretical understanding of semiconductor behavior but also translates into practical benefits in the industry.

Despite the advantages offered by Ridge Regression in addressing multicollinearity in the context of Electrical Performance Prediction in Semiconductor Devices, the proposed method is not without its limitations. One significant drawback is the dependency on the appropriate selection of the regularization parameter, λ, which can substantially influence the model's performance; an incorrectly chosen λ may lead to either underfitting or overfitting, potentially skewing the predictions of key parameters like saturation current and leakage current. Additionally, while Ridge Regression mitigates the impact of multicollinearity by shrinking the coefficients, it does not eliminate it; thus, interpretations of the coefficients remain complicated, as the true relationships among the predictors might be obscured. Furthermore, Ridge Regression assumes that all included variables contribute to the outcome, potentially leading to model misspecification if irrelevant predictors are included or relevant ones omitted, which could result in biased estimates. Moreover, the regularization process imposes a form of bias on the estimates, which, while beneficial in reducing variance, could hinder the ability to achieve the most accurate forecasting in scenarios where the relationships among predictors are indeed non-linear or more complex than the linear assumption of the model allows. Finally, the method may not adequately capture the intricate nuances of semiconductor physics, especially in highly dynamic environments where physical models might be essential for understanding phenomena beyond statistical correlations, suggesting that supplementary methodologies should be explored to fully harness the complexities of semiconductor device performance modeling.

6. Conclusion

In this study, we have presented a novel Ridge Regression-based method for predicting electrical performance in semiconductor devices, aiming to address the current lack of a comprehensive approach for precise prediction in this field. The innovative aspect of our work lies in the utilization of Ridge Regression, which effectively balances model complexity and prediction accuracy, thus improving the accuracy of electrical performance prediction and offering insights into the underlying factors influencing device performance. Our research contributes to the advancement of semiconductor device design and optimization by providing a robust and efficient prediction model. However, this study is not without limitations. One potential limitation is the reliance on a specific machine learning technique, which may not be optimal for all types of semiconductor devices. In future work, exploring the integration of multiple machine learning algorithms or incorporating domain knowledge could further enhance the prediction accuracy and generalizability of the model. Additionally, expanding the dataset to include a wider range of semiconductor devices and operating conditions would increase the model's applicability across different scenarios. Overall, the findings presented in this paper open up new possibilities for enhancing the prediction of electrical performance in semiconductor devices and pave the way for further research in this area.

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Conceptualization, E. M. and L. T.; writing—original draft preparation, E. M. and S. C.; writing—review and editing, L. T. and S. C.; All of the authors read and agreed to the published the final manuscript.

Data Availability Statement

The data can be accessible upon request.

Conflict of Interest

The authors confirm that there are no conflict of interests.

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