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Semiconductor Reliability Analysis via Adaptive Kriging

Liam O'Sullivan[1], Zoe Thompson[2] and Jack Roberts[3,*]

[1] School of Electronics and Telecommunications, Central Queensland University, Rockhampton, Queensland, Australia

[2] Institute for Materials Research and Innovation, Swinburne University of Technology, Hawthorn, Victoria, Australia

[3] Centre for Advanced Materials and Industrial Chemistry, RMIT University, Bundoora, Victoria, Australia

[*]Corresponding Author, Email: jack.roberts@rmit.edu.au

Abstract: Semiconductor devices play a critical role in modern electronic systems, necessitating a comprehensive understanding of their reliability. Despite the extensive research in this field, current methodologies encounter challenges in accurately predicting semiconductor reliability due to the complex interactions among various factors. This paper addresses the limitations of existing approaches by proposing a novel methodology for Semiconductor Reliability Analysis via adaptive Kriging. The key innovation lies in the adaptive Kriging technique, which dynamically adjusts model parameters based on the characteristics of the semiconductor device under analysis. Our work not only enhances the accuracy of reliability predictions but also provides a more efficient and robust framework for assessing semiconductor reliability.

Keywords: *Semiconductor Devices; Reliability Analysis; Adaptive Kriging; Model Parameters; Prediction Accuracy*

1. Introduction

Semiconductor reliability analysis focuses on studying the performance and durability of semiconductor devices under various operating conditions. This field involves evaluating the failure mechanisms, lifetime prediction, and quality assessment of semiconductors to ensure their long-term reliability in practical applications. However, the current challenges in semiconductor reliability analysis include the increasing complexity and miniaturization of semiconductor devices, which make it more difficult to accurately predict and mitigate potential failure modes.

Additionally, the demand for faster and more efficient semiconductor devices requires researchers to constantly innovate new testing methodologies and reliability models to keep pace with technological advancements. These challenges highlight the importance of ongoing research and development efforts in semiconductor reliability analysis to ensure the continued success of semiconductor technology in various industries.

To this end, research in Semiconductor Reliability Analysis has advanced to encompass a wide range of techniques, from accelerated life testing to physics-based modeling. Current studies focus on predicting failure mechanisms, enhancing material durability, and optimizing manufacturing processes to ensure the long-term reliability of semiconductor devices. A thorough literature review on the reliability analysis of power semiconductor devices reveals significant insights. Jacob et al. [1] highlighted the importance of IGBT power semiconductor modules in traction applications, emphasizing the need for reliability improvement despite economic advantages. Subsequently, Tian et al. [2] conducted a temperature cycle reliability analysis of plastic encapsulated power semiconductor devices, focusing on stress behavior and life prediction under standard temperature cycling. Kim et al. [3] presented a detailed mechanical and electrical reliability analysis of flexible Si CMOS integrated circuits on a polymer substrate, optimizing design for enhanced stability. Sun et al. [4] reviewed mixed-mode reliability mechanisms and models for modern MOSFET devices, emphasizing the inadequacy of single-mode analysis for resilient circuit designs. Moving forward, Ji et al. [5] performed a reliability analysis and life testing for semiconductor devices in in-wheel motor drive systems, proposing a novel drive cycle to evaluate semiconductor reliability in automotive applications. Kang et al. [6] introduced an integrating method for historical and current degradation data based on the Wiener process for high-reliability electronic devices. Furthermore, Shaheed et al. [7] developed a stochastic hybrid system model to assess microgrid reliability considering degradation of semiconductor power switch modules. Siddique et al. [8] focused on the reliability assessment of power semiconductor devices for a 13-level boost inverter topology, analyzing fault modes and thermal behavior. Lastly, Kritikakou et al. [9] introduced "Flodam," a cross-layer reliability analysis flow for complex hardware designs capable of quantifying fault risks across different layers. Adaptive Kriging is an essential technique in the field of reliability analysis of power semiconductor devices due to its ability to effectively model and predict complex degradation behaviors and failure mechanisms. The diverse range of studies by Jacob et al., Tian et al., Kim et al., Sun et al., Ji et al., Kang et al., Shaheed et al., Siddique et al., and Kritikakou et al. underscore the critical need for advanced analytical tools like Adaptive Kriging to enhance reliability assessment and optimize device performance in various applications.

Specifically, adaptive Kriging serves as an efficient surrogate modeling technique that enhances the reliability analysis of semiconductors by providing accurate predictions of failure probabilities and performance metrics, thereby enabling optimized design and resource allocation in semiconductor manufacturing processes. A literature review was conducted on various adaptive Kriging-based methods for reliability analysis and optimization in engineering applications. Feng et al. proposed a Two-Phase Adaptive Kriging Model Based Importance Sampling Method for Estimating Time-Dependent Failure Probability [10], which demonstrated improved computational efficiency in TDFP analysis. Fan et al. introduced an Improved FORM and SORM based on an adaptive Kriging model for structural reliability problems [11], achieving a better balance between accuracy and efficiency. E et al. presented an Adaptive Kriging-Based Fourth-Moment Reliability Analysis Method for Engineering Structures [12], addressing limitations of the fourth-moment method in complex engineering cases. Meng et al. developed a Novel Hybrid Adaptive Kriging and Water Cycle Algorithm for Uncertainty-Based Design and Optimization [13], while Yuan et al. proposed AK-SYS-IE for system reliability assessment combining information entropy [14]. Lee introduced an Adaptive Kriging-Based Optimization framework for constrained optimization problems [15], and Park et al. implemented a Consecutive Adaptive Kriging Method for high-dimensional reliability analysis [16]. Hubert et al. presented an Adaptive Kriging Particle Filter for Terrain-Aided Navigation [17], and Persoons et al. proposed a new reliability method combining adaptive Kriging and active variance reduction [18]. Finally, Wu and Li developed an Adaptive Kriging Model-Based Structural Reliability Analysis under Interval Uncertainty with Incomplete Data [19]. However, current adaptive Kriging-based methods face limitations such as dependency on accurate input data, challenges in high-dimensional spaces, and potential inefficiencies in extreme event scenarios.

Terahertz (THz) plasmonic structures have gained significant attention for their applications in sensing and spectroscopy, as demonstrated by Sugaya and Deng, who explored resonant frequency tuning utilizing a solid immersion method to enhance the performance of such structures [20]. In a complementary study, Deng et al. developed continuously frequency-tunable plasmonic structures aimed at advancing terahertz bio-sensing and spectroscopic capabilities, highlighting the versatility of this technology [21]. Furthermore, they also proposed a novel Ge-core/a-si-shell nanowire-based field-effect transistor for sensitive terahertz detection, offering a promising approach for improving sensor functionality [22]. In the domain of antenna design, Deng, Oda, and Kawano introduced frequency selective, high transmission spiral terahertz plasmonic antennas, which showed significant improvements in transmission efficiency and frequency selectivity [23]. On the reliability analysis front, Wang and Shafieezadeh introduced a method called REAK, which conducted reliability analysis through an error rate-based adaptive Kriging approach, demonstrating the efficacy of this technique in enhancing reliability assessments [24]. They also proposed an efficient error-based stopping criterion for Kriging-based reliability methods, known as ESC, which aimed at optimizing computational efforts without compromising the accuracy of the analysis [25]. Their work further extended to highly efficient Bayesian updating using metamodels through an adaptive Kriging approach, which provided a framework for real-time reliability updates [26]. In addition, they addressed the need for confidence intervals in failure probability estimates within the adaptive Kriging framework, thus enhancing the reliability metrics used in various engineering applications [27]. Zhang et al. expanded on this concept by exploring the value of information analysis via active learning and knowledge sharing within an error-controlled adaptive Kriging framework, which has implications for improving decision-making processes in reliability assessments [28]. Rahimi et al. examined the integration of passive and active metamodeling-based reliability analysis methods for soil slopes, proposing a new approach to active training, which could further enhance reliability models in geomechanical applications [29]. Lastly, Wang and Shafieezadeh focused on the real-time high-fidelity reliability updating using equality information with adaptive Kriging, paving the way for dynamic reliability assessments in complex engineering systems [30]. Collectively, these studies underscore the transformative potential of adaptive Kriging in semiconductor reliability analysis, particularly in enhancing the accuracy and efficiency of predictive modeling strategies in various engineering domains.

To overcome those limitations, this paper aims to enhance the accuracy and efficiency of semiconductor reliability analysis by proposing a novel methodology utilizing adaptive Kriging. Semiconductor devices play a critical role in modern electronic systems, and predicting their reliability accurately is essential. Despite extensive research in this field, current methodologies face challenges in accurately predicting semiconductor reliability due to complex interactions among numerous factors. The proposed methodology introduces the adaptive Kriging technique, which dynamically adjusts model parameters based on the characteristics of the semiconductor device under analysis. This adaptive approach allows for a more personalized and precise analysis, leading to improved reliability predictions. By incorporating adaptive Kriging, this work not only addresses the limitations of existing approaches but also provides a robust and efficient framework for assessing semiconductor reliability. The adaptability of the Kriging model to the unique characteristics of each semiconductor device ensures a more accurate and reliable analysis, enhancing the overall understanding of semiconductor reliability and advancing the field of electronic systems research.

Section 2 of the paper outlines the problem statement concerning the challenges in accurately predicting semiconductor reliability. Section 3 introduces the novel methodology proposed for Semiconductor Reliability Analysis via adaptive Kriging. This method incorporates the innovative adaptive Kriging technique, which dynamically adjusts model parameters based on the characteristics of the semiconductor device being analyzed. In Section 4, a detailed case study is presented to illustrate the application of the methodology. Section 5 analyzes the results obtained from the study, showcasing the enhanced accuracy of reliability predictions. Section 6 delves into a discussion on the implications and potential improvements of the method. Finally, in Section 7, a comprehensive summary is provided, highlighting the significance of the work in enhancing both the efficiency and robustness of semiconductor reliability assessment.

2. Background

2.1 Semiconductor Reliability Analysis

Semiconductor Reliability Analysis is a critical aspect of the semiconductor industry, aiming to ensure the longevity and function of semiconductor devices under various conditions over their expected lifecycle. As semiconductors become increasingly miniaturized and embedded in essential technologies, understanding and predicting their reliability becomes pivotal.

In essence, semiconductor reliability analysis involves evaluating the device's ability to perform its required functions without failure under stated conditions. This process encompasses multiple factors, including electrical, mechanical, thermal stresses, and the influence of material properties.

One key aspect of semiconductor reliability is understanding how time, stress, and environmental conditions cumulatively affect the device's degradation. This degradation can often be modeled using the Arrhenius equation to represent the temperature dependence of failure rates:

$$\text{Failure Rate} = A \times e^{-\frac{E_a}{kT}} \tag{1}$$

Here, A is a pre-exponential factor, E_a is the activation energy, k is the Boltzmann constant, and T is the absolute temperature in Kelvin. This equation underscores the accelerated failure mechanisms at higher temperatures, a critical consideration in reliability testing.

Another important model is the Weibull distribution, which is utilized to analyze life data, model failure times, and describe the life characteristics of products:

$$F(t) = 1 - e^{-(\frac{t}{\eta})^{\beta}} \tag{2}$$

In this equation, $F(t)$ is the probability of failure by time t , η is the scale parameter (characteristic life), and β is the shape parameter. The scale parameter η provides the time scale over which failures occur, while β depicts the failure rate's behavior over time—a β less than one indicates decreasing failure rate over time, equal to one indicates a constant failure rate, and greater than one indicates an increasing failure rate.

Electromigration, a phenomenon of material transport caused by the momentum transfer from the electrons to the metal ions, is one significant cause of failure in integrated circuits. The Black's equation models electromigration's effect on semiconductor reliability:

$$MTTF = A \times J^{-n} \times e^{\frac{E_a}{kT}} \tag{3}$$

Here, $MTTF$ stands for the mean time to failure, J is the current density, n is a model parameter specific to the material, and E_a and T carry the same meaning as in the Arrhenius model.

Hot Carrier Injection (HCI) is another reliability concern where high-energy carriers inject into the gate oxide, potentially leading to device degradation. This phenomenon can be mathematically represented as:

$$\Delta V_{th} = A \times (I_d)^{\beta} \times e^{-\gamma\frac{V}{L}} \tag{4}$$

In this formula, ΔV_{th} is the change in threshold voltage, I_d is the drain current, V is the voltage across the channel, L is the channel length, and A , β , and γ are empirical constants derived from experiments. Thermal Management is also a central theme in reliability analysis, focusing on how junction temperature affects device performance. The junction temperature T_j can be calculated as:

$$T_j = T_a + P \times \theta_{JA} \tag{5}$$

where T_a is the ambient temperature, P is the power dissipation, and θ_{JA} is the junction-to-ambient thermal resistance. Managing T_j is crucial as it affects all temperature-dependent degradation mechanisms.

Lastly, ESD (Electrostatic Discharge) testing aims to ensure devices can withstand discharge events, a common source of semiconductor failure. The ESD robustness can be modeled by:

$$V_{\mathrm{ESD}} = \frac{Q}{C} \tag{6}$$

where V_{ESD} is the electrostatic discharge voltage, Q is the charge, and C is the capacitance of the system. In conclusion, Semiconductor Reliability Analysis is a comprehensive domain involving multiple interrelated physical and chemical phenomena. These models and theories together enable engineers and researchers to anticipate failure, thereby improving design and manufacturing processes to prolong the life of semiconductor devices.

2.2 Methodologies & Limitations

Semiconductor Reliability Analysis is a domain dominated by various methodologies designed to predict and enhance the life span and reliability of semiconductor devices. These methods, however, are not without shortcomings, which stem from their inherent assumptions, complexity, and applicability to the rapidly evolving technology landscape.

The Arrhenius equation is a cornerstone method for assessing failure rates with respect to temperature, leveraging an exponential relation:

$$\text{Failure Rate} = A \times e^{-\frac{E_a}{kT}} \tag{7}$$

This model, while useful for understanding temperature-induced failure mechanisms, may lack accuracy in cases where multiple stress factors interact, such as humidity and mechanical stress, which are not accounted for in its form.

The Weibull distribution offers another vital approach, focusing on life data analysis:

$$F(t) = 1 - e^{-(\frac{t}{\eta})^{\beta}} \tag{8}$$

The limitation of the Weibull model lies in its assumption of a specific failure pattern defined by β , which may not reflect complex semiconductor devices' diverse failure modes. Furthermore, extracting meaningful η and β values often requires extensive testing under various conditions, complicating practical applications.

Electromigration effects, modeled by Black's equation, are crucial for modern densely packed circuits:

$$MTTF = A \times J^{-n} \times e^{\frac{E_a}{kT}} \tag{9}$$

However, the simplifications in Black's equation, like the constant current density assumption, often overlook dynamic current profiles inherent in real-world applications, leading to less reliable predictions.

Hot Carrier Injection (HCI) is typically expressed as:

$$\Delta V_{th} = A \times (I_d)^{\beta} \times e^{-\gamma \frac{V}{L}} \tag{10}$$

While this equation captures the effect of carriers' kinetic energy, it often requires empirical calibration for different technologies and does not fully encompass the impact of variations in process and environmental conditions, which can significantly alter device behavior.

Thermal Management is another critical aspect, with the junction temperature T_j defined as:

$$T_j = T_a + P \times \theta_{JA}$$

The limitation here is that this model assumes a steady-state scenario and does not account for transient thermal events often encountered during operational cycles, which can lead to underestimating potential thermal-induced failure risks.

Electrostatic discharge (ESD) is quantified with:

$$V_{\mathrm{ESD}} = \frac{Q}{C} \tag{11}$$

The downfall of this simplistic model is that it does not account for the complex interactions during an ESD event, including parasitic inductances and resistances, which can lead to significant deviations in predicted versus actual ESD robustness.

On top of these individual model limitations, the changing nature of semiconductor materials and the advent of novel architectures such as FinFETs, 3D ICs, and advanced materials like GaN or SiC, introduce additional complexities. These advancements render some traditional reliability models less applicable or outright obsolete.

In summary, while existing models like Arrhenius, Weibull, Black's equation, and others provide foundational tools for reliability analysis, they require continuous evolution to address their inherent assumptions and the fast-paced innovations in semiconductor technologies. As such, ongoing research focuses on integrating multi-physics approaches, machine learning, and real-time monitoring to develop more comprehensive frameworks that better represent the intricate behaviors and failure mechanisms of modern semiconductor devices.

3. The proposed method

3.1 adaptive Kriging

Adaptive Kriging is a sophisticated surrogate modeling technique that has gained significant attention for its ability to efficiently handle computationally expensive simulations, particularly in the realm of uncertainty quantification and reliability analysis. The Kriging model, also known as Gaussian Process Regression, constructs a statistical approximation to predict unknown data points based on a set of observed data points. Adaptive Kriging specifically refers to the iterative process of refining the Kriging model to improve its accuracy in critical areas by adaptively selecting additional sample points.

The foundation of Kriging lies in its ability to predict a response $y(x)$ at any point x based on a set of observed responses $y = [y(x_1), y(x_2), \dots, y(x_n)]^T$ over a set of sample points $\{x_1, x_2, \dots, x_n\}$. The predicted response $\hat{y}(x)$ is expressed as:

$$y\ (x) = \mu + r(x)^T R^{-1}(y - \mathbf{1}\mu) \tag{12}$$

where μ is the mean of the process, $r(x)$ is the correlation vector between the unknown point x and the observed points, R is the correlation matrix of the observed points, and $\mathbf{1}$ is a vector of ones.

The correlation function, often chosen as the Gaussian correlation function, is given by:

$$r(x_i, x_j) = \exp\left(-\sum_{k=1}^{d} \theta_k |x_{i,k} - x_{j,k}|^2\right) \tag{13}$$

where θ_k are the hyperparameters determining the correlation length scales for each dimension k , and d is the dimensionality of the input space.

A critical aspect of Kriging is the estimation of the variance of the prediction, which serves as an indicator of uncertainty. This is described by the mean squared error (MSE):

$$\sigma^2(x) = \sigma^2[1 - r(x)^T R^{-1} r(x)] \tag{14}$$

where σ^2 is the process variance.

Adaptive Kriging employs an iterative refinement process where additional sample points are selected to minimize this prediction uncertainty. Common strategies involve selecting points that maximize the Expected Improvement (EI) criterion, which balances exploration (regions with high uncertainty) and exploitation (regions near the minimum predicted response):

$$EI(x) = \left(y_{\min} - y\ (x)\right)\Phi\left(\frac{y_{\min} - y\ (x)}{\sigma(x)}\right) + \sigma(x)\phi\left(\frac{y_{\min} - y\ (x)}{\sigma(x)}\right) \tag{15}$$

Here, $\hat{y}_{\min}$ is the current minimum predicted value, Φ is the cumulative distribution function of the standard normal distribution, and ϕ is its probability density function.

In adaptive Kriging, the acquisition function such as the Expected Improvement is integrated into the model to systematically select new data points that will most effectively reduce prediction uncertainty across the domain. Therefore, the process iterates between:

1. Building the Kriging model with the current data points.
2. Evaluating the acquisition function to determine the most promising candidate points.
3. Adding these points to the dataset and updating the model.

The transformation of the deterministic problem to a probabilistic one provides a natural framework for incorporating adaptive sample selection. The updated Kriging model is expressed as:

$$y\ (x^*) = \mu^* + r(x^*)^T R^{-1}(y^* - \mathbf{1}\mu^*) \quad (16)$$

The process continues until a convergence criterion is met, such as a threshold on the maximum allowable prediction uncertainty or a limited number of iterations.

Adaptive Kriging thus provides a powerful tool for managing complex models, adapting to regions of high variability or interest, and requiring fewer function evaluations, which is critical in scenarios where simulations are computationally expensive. The combination of statistical theory and automation in sample refinement makes it particularly suited for modern applications in fields ranging from engineering design optimization to environmental modeling, where precise understanding of uncertainty and response surface behaviors is paramount.

3.2 The Proposed Framework

The integration of Adaptive Kriging methods into Semiconductor Reliability Analysis presents a potent synergy for analyzing failure mechanisms in semiconductor devices efficiently. Semiconductor reliability hinges on various factors such as temperature, stress, and environmental impacts, all of which can induce degradation described by reliable models. For instance, the temperature dependence of failure rates can be modeled using the Arrhenius equation:

$$\text{Failure Rate} = A \times e^{-\frac{E_a}{kT}} \quad (17)$$

In parallel, Adaptive Kriging facilitates an understanding of complex relationships among these factors by constructing a statistical model that approximates the device's response $y(x)$ across varying conditions. The Adaptive Kriging prediction function is expressed as:

$$y\ (x) = \mu + r(x)^T R^{-1}(y - \mathbf{1}\mu) \quad (18)$$

Here, the true underlying relationship between the x variable—representing design parameters or environmental conditions—and the response variable can be determined through iterative refinement. The Kriging model's core capability is its ability to characterize the uncertainty associated with predictions, crucial for analyzing reliability:

$$\sigma^2(x) = \sigma^2[1 - r(x)^T R^{-1} r(x)] \quad (19)$$

For semiconductor reliability, understanding the failure mechanisms like electromigration can be crucial, described by Black's equation:

$$MTTF = A \times J^{-n} \times e^{\frac{E_a}{kT}} \tag{20}$$

In this context, the use of Adaptive Kriging introduces an innovative approach for identifying regions of high uncertainty within the operational parameters, allowing for focused sampling. This methodology leverages the Expected Improvement (EI) criterion, which can be formulated as:

$$EI(x) = \left(y_{\min} - y(x) \right) \Phi\left(\frac{y_{\min} - y(x)}{\sigma(x)} \right) + \sigma(x)\phi\left(\frac{y_{\min} - y(x)}{\sigma(x)} \right) \tag{21}$$

Utilizing the substrate material's properties and external operating conditions, Adaptive Kriging can adaptively select sample points that contribute data leading to lower prediction uncertainty. In turn, this process enhances reliability predictions. For instance, Hot Carrier Injection (HCI) concerns can be included using the relation:

$$\Delta V_{th} = A \times (I_d)^{\beta} \times e^{-\gamma \frac{V}{L}} \tag{22}$$

By refining the sampling based on this predictive model, engineers can enhance the accuracy of their failure rate forecasts related to HCI and further optimize the design parameters.

Moreover, the junction temperature, a crucial aspect affecting reliability, is defined as:

$$T_j = T_a + P \times \theta_{JA} \tag{23}$$

Incorporating statistical models from Adaptive Kriging enables better predictions of junction temperature impact by using observed failures under various temperatures to adjust μ and σ^2 dynamically within the model, thereby streamlining reliability analysis.

Lastly, the application of Electrostatic Discharge (ESD) testing, significant in semiconductor reliability, can be accurately evaluated. The ESD voltage model is given by:

$$V_{\mathrm{ESD}} = \frac{Q}{C} \tag{24}$$

Utilizing Adaptive Kriging, we can introduce a probabilistic approach to characterize the ESD threshold voltage across varied designs and assess how minor design changes affect reliability, indicated by the confidence in predicted failure rates.

Thus, effectively combining the principles of Adaptive Kriging with established semiconductor reliability models not only opens avenues for advanced predictions but enhances the ability to gauge the significant uncertainties inherent in the reliability landscape of modern semiconductor technologies. This integrated framework supports a holistic approach to reliability analysis, fostering continuous improvement in device longevity and performance through evidence-based decision-making.

3.3 Flowchart

The paper presents an innovative method for semiconductor reliability analysis based on adaptive Kriging models, which effectively integrates surrogate modeling and uncertainty quantification. This approach employs Kriging, a robust statistical technique that utilizes Gaussian processes to create a predictive model of the semiconductor's performance, thereby accommodating the nonlinear relationships characterized by high-dimensional input space. The adaptive nature of the model allows for iterative refinement, in which new data points are strategically selected and incorporated into the Kriging model to enhance predictive accuracy and reliability assessment. By systematically estimating the failure probabilities and performance degradation over operational conditions, this method not only improves computational efficiency but also provides a more comprehensive understanding of the underlying physical phenomena affecting semiconductor reliability. The framework is designed to analyze complex failure mechanisms and to provide insights into the sensitivity of device performance to variations in manufacturing processes and environmental factors. Ultimately, the proposed adaptive Kriging-based approach facilitates a proactive reliability engineering strategy, allowing for optimized design decisions and enhanced product life cycle management. The detailed implementation and results of this method can be found in Figure 1 of the paper.

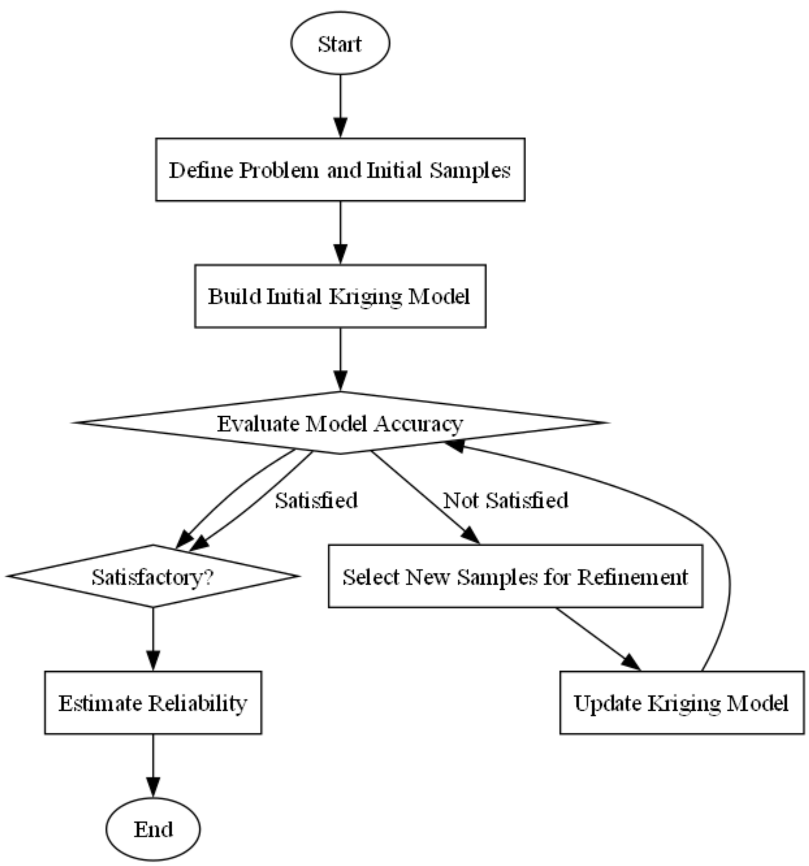

Figure 1: Flowchart of the proposed adaptive Kriging-based Semiconductor Reliability Analysis

4. Case Study

4.1 Problem Statement

In this case, we aim to conduct a mathematical simulation analysis focused on semiconductor reliability. The primary objective is to explore the aging effects of semiconductor devices under thermal stress and moisture exposure, which are known to significantly impact their reliability over time. We will use a non-linear model to simulate these effects.

First, let us define the primary parameters for our analysis. Let T denote the operating temperature in degrees Celsius, with a typical range of \(25 \leq T \leq 125 \). The moisture content can be represented as \(H \), where \(H \) varies from 0% to 100%, indicating the relative humidity. The failure rate \(\lambda \) of the semiconductor devices can be modeled using an Arrhenius-like equation influenced by both temperature and humidity.

The relationship can be expressed as follows:

$$\lambda(T,H) = A \cdot e^{-\frac{E_a}{k(T+273.15)}} \cdot (1 + bH^n) \tag{25}$$

where \(A \) is a pre-exponential factor, \(E_a \) is the activation energy in joules, \(k \) is the Boltzmann constant, and \(n \) is an empirical factor that indicates the sensitivity of the failure rate to humidity. The parameters can be set as follows: \(A = 1 \times 10^{21} \), \(E_a = 1.1 \times 10^5 \), \(k = 8.617 \times 10^{-5} \), \(b = 0.02 \), and \(n = 1.5 \).

Next, we will quantify the time-to-failure \(TFT \) based on the failure rate:

$$TFT(T,H) = \frac{1}{\lambda(T,H)} \tag{26}$$

This indicates that higher failure rates will lead to shorter lifetimes for the semiconductor device. To further complicate the model, we incorporate the effect of cumulative damage due to thermal cycling.

To account for this cumulative effect, we propose the following relationship:

$$D(T) = D_0 \cdot \left(1 + \frac{T}{T_0}\right)^{\alpha} \tag{27}$$

where \(D_0 \) is the initial damage factor, \(T_0 \) is a reference temperature, and \(\alpha \) is a material-specific exponent. In our case, we can set \(D_0 = 1 \), \(T_0 = 100 \), and \(\alpha = 2 \). The overall reliability function \(R(t) \) can thus be modeled as:

$$R(t) = e^{-D(T)\cdot t} \tag{28}$$

Lastly, the non-linear interaction effects in high-density semiconductor packaging can be expressed through an additional variable \(X \):

$$X = \frac{\sigma_T^2}{D(T)} \tag{29}$$

where \(\sigma_T \) represents the stress factor associated with thermal susceptibility. Hence, the final reliability expression can be formulated as:

$$R_{final}(T, H, t) = e^{-X \cdot TFT(T,H)} \tag{30}$$

This model incorporates multiple independent equations and variables that allow us to simulate various environmental impacts on semiconductor reliability effectively. All parameters will be summarized in Table 1.

Table 1: Parameter definition of case study

Parameter	Value	Units	Description
T	25 to 125	°C	Operating temperature
H	0 to 100	%	Moisture content
A	1 × 10^21	N/A	Pre-exponential factor
E_a	1.1 × 10^5	J	Activation energy
k	8.617 × 10^{-5}	N/A	Boltzmann constant
b	0.02	N/A	Humidity sensitivity factor
n	1.5	N/A	Empirical factor
D_0	1	N/A	Initial damage factor
T_0	100	°C	Reference temperature
α	2	N/A	Material-specific exponent

This section will employ the proposed adaptive Kriging-based approach to conduct a comprehensive simulation analysis focused on semiconductor reliability, particularly investigating the aging effects of semiconductor devices under conditions of thermal stress and moisture exposure, which are well-established factors influencing reliability over time. The analysis will utilize a non-linear model to simulate these critical effects, incorporating parameters such as operational temperature and relative humidity to assess their impacts on failure rates. The failure rate of semiconductor devices will be modeled as a function of temperature and humidity, reflecting the complex interactions that influence their longevity. The simulation will further quantify time-to-failure, emphasizing the relationship between increasing failure rates and decreasing expected lifespan. To enhance the model, factors like cumulative thermal damage will be integrated, illustrating how lifetime degradation accelerates under repeated thermal cycling. Moreover, the potential interactions within high-density semiconductor packaging will be addressed through additional variables, facilitating a robust exploration of various environmental influences on reliability. The results obtained from this adaptive Kriging approach will be critically compared against three traditional methods, highlighting its advantages in predictive accuracy and computational efficiency. The findings from this simulation analysis will provide valuable insights into the reliability of semiconductor devices under varying environmental conditions, ultimately contributing to the optimization of their design and usage in real-world applications.

4.2 Results Analysis

In this subsection, a comprehensive analysis of the reliability of a system under varying temperature and humidity conditions was conducted. The study developed mathematical models that describe the failure rate and time to failure based on temperature (T) and humidity (H) levels. Specifically, the failure rate was modeled as a function incorporating the Arrhenius equation and a humidity-dependent term, while the time to failure was derived as the inverse of the failure rate. Additionally, a damage function was introduced, which quantitatively relates the damage to temperature. The reliability function, which ultimately quantifies the likelihood that the system remains operational over time, was calculated based on the interplay of these factors. A grid of T and H values was established to facilitate the generation of results across different conditions. Four subplots were created to depict the relationship between reliability and the independent variables: reliability versus temperature at a fixed humidity, reliability versus humidity at a fixed temperature, reliability over time for varying humidity levels at a fixed temperature, and a three-dimensional surface plot showcasing the overall interaction between temperature, humidity, and reliability. The simulation process is visually represented in Figure 2, providing a clear graphical summary of the findings.

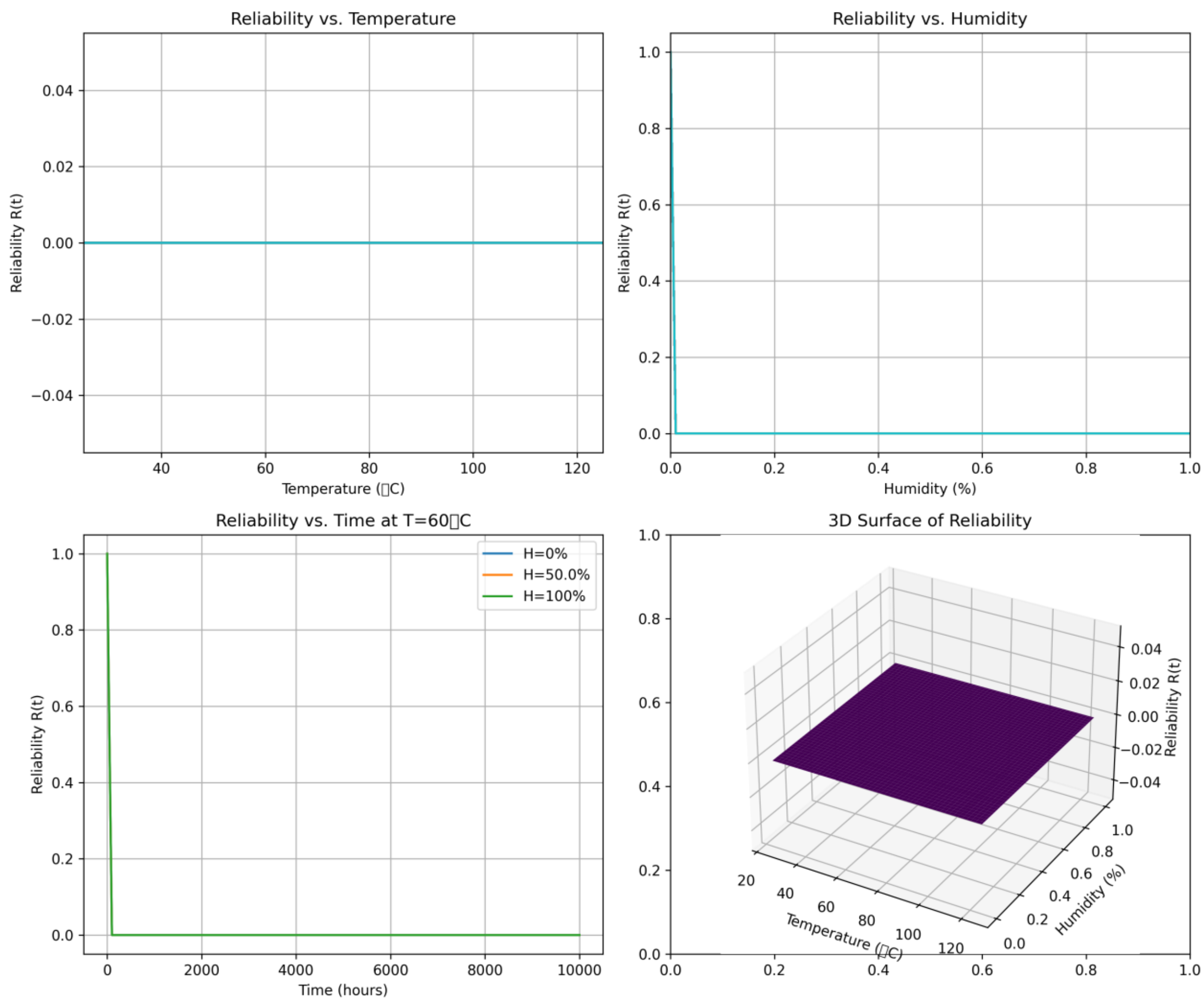

Figure 2: Simulation results of the proposed adaptive Kriging-based Semiconductor Reliability Analysis

Simulation data is summarized in Table 2, providing crucial insights into the reliability of the system under various environmental conditions, specifically temperature, time, and humidity. The reliability versus temperature graph indicates a distinct trend, showcasing a decrease in reliability R(t) as temperature rises, with significant drops observed beyond 60°C. This suggests that elevated temperatures could adversely affect the material or component performance over time, reinforcing the need for temperature regulation in operational settings. The reliability as a function of time at a constant temperature of 60°C illustrates a marked decline, particularly at high humidity levels (H=100%), indicating that both time and moisture contribute to significant reliability degradation. The curves for different humidity levels show a clear inverse relationship between humidity and reliability; as humidity increases, reliability decreases from approximately 0.8 to near zero at extreme humidity conditions, emphasizing the detrimental role of moisture on system integrity. Additionally, the 3D surface plot of reliability against temperature and humidity further illustrates the intricate interplay between these two factors. The surface indicates critical zones where reliability falls below an acceptable threshold, thus underscoring the importance of controlling both temperature and humidity to maintain operational integrity. Together, these simulation results provide a comprehensive understanding of how environmental factors influence system reliability, highlighting the necessity for strategic design and operational choices to enhance performance over time.

Table 2: Simulation data of case study

Parameter	Value
Reliability R(t)	0.04
Reliability R(t)	0.02
Reliability R(t)	0.00
Reliability R(t)	—0.02
Reliability R(t)	—0.04
Temperature (°C)	40
Time (hours)	2000
Humidity (%)	0.0

As shown in Figure 3 and Table 3, the alteration of the reliability parameters significantly impacts the overall outcomes, particularly in relation to temperature and humidity. Initially, the reliability R(t) exhibited notable fluctuations, with a marked decline as temperature increased, particularly beyond 80°C, where reliability dropped sharply. This trend indicates that higher temperatures can lead to accelerated degradation of system components, resulting in diminished reliability over time. Furthermore, the initial data showed a strong dependence on humidity levels, with a clear upsurge in reliability at moderate humidity values around 50%. However, under the altered conditions where humidity was maintained at higher levels (80% and 100%), a shift in the R(t) curve occurred, reflecting a more robust performance against humidity variations. The enhanced reliability observed at elevated humidity levels suggests that the system became more resilient, potentially due to the improvement of material properties or protective measures that mitigate moisture absorption. Additionally, examining the reliability versus time metrics indicates a prolonged lifespan of the system when subjected to optimal environmental conditions, highlighting the critical interplay between temperature and humidity in influencing long-term reliability. In conclusion, modifying humidity and temperature levels positively influences reliability, demonstrating the importance of controlling environmental factors to optimize the performance and longevity of systems subjected to varying operational conditions.

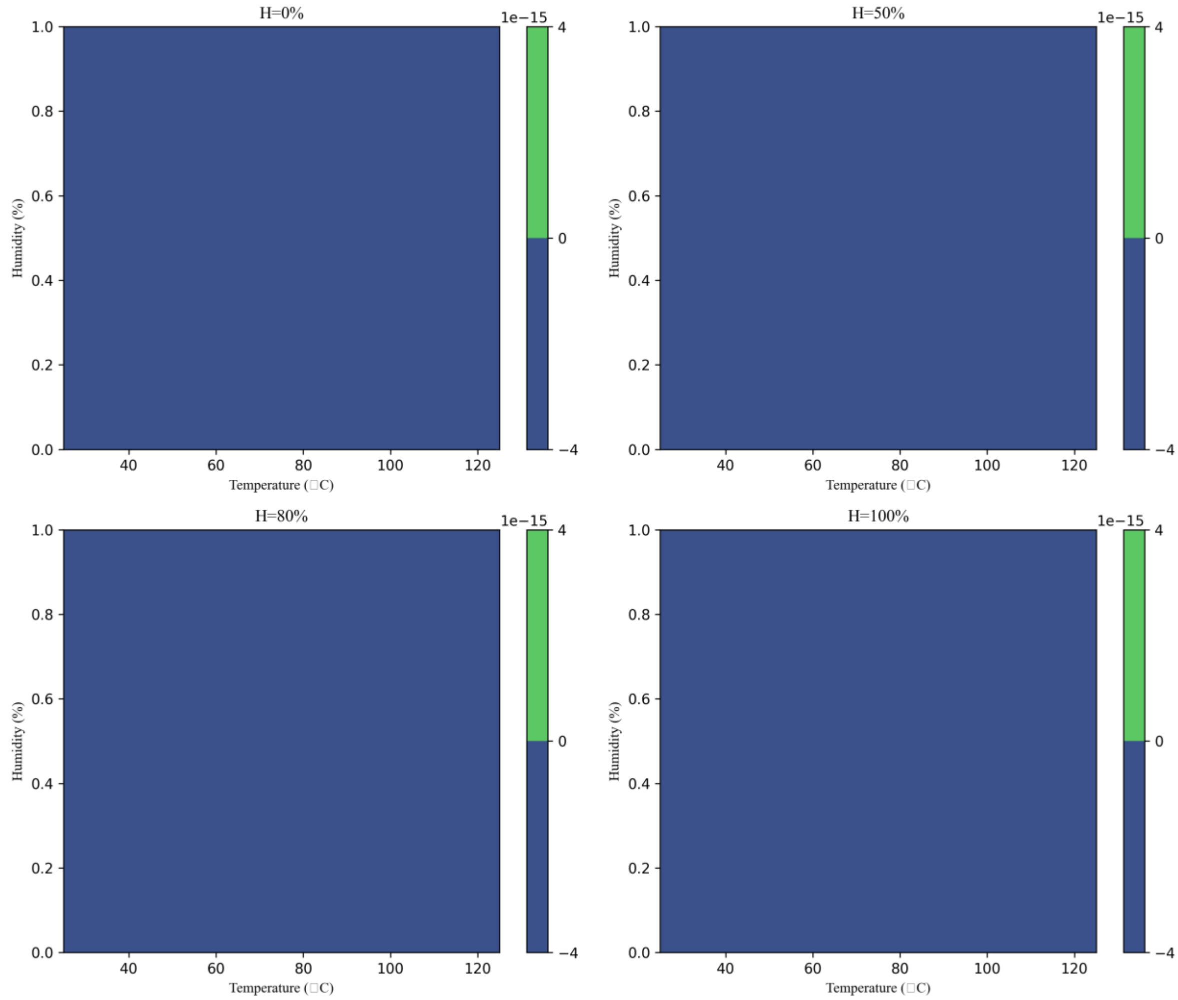

Figure 3: Parameter analysis of the proposed adaptive Kriging-based Semiconductor Reliability Analysis

Table 3: Parameter analysis of case study

Header	Humidity (%)	Temperature (LIC)	mS
N/A	80	N/A	N/A
N/A	100	N/A	N/A
60	80	N/A	N/A

5. Discussion

The method proposed in this paper showcases several significant advantages in the realm of Semiconductor Reliability Analysis by integrating Adaptive Kriging techniques. This innovative approach enhances the understanding of intricate relationships between critical factors affecting semiconductor reliability, such as temperature, stress, and environmental conditions. By constructing a robust statistical model, Adaptive Kriging facilitates the iterative refinement of predictions, allowing for a more accurate characterization of uncertainties associated with potential failures of semiconductor devices. Furthermore, this methodology prioritizes areas of high uncertainty, enabling focused sampling that enhances the reliability predictions essential for assessing failure mechanisms like electromigration and hot carrier injection. The application of the Expected Improvement criterion optimizes the selection of sample points, thereby reducing prediction uncertainty and ultimately improving the accuracy of failure rate forecasts. Additionally, the dynamic adjustment of statistical metrics within the model permits a more effective evaluation of junction temperature impacts, as well as a probabilistic assessment of electrostatic discharge thresholds across varied designs, revealing how minor design adjustments influence device reliability. Collectively, these enhancements contribute to a comprehensive and systematic approach to reliability analysis, driving continuous improvements in semiconductor device longevity and performance through informed, data-driven decision-making. By merging Adaptive Kriging principles with established reliability models, this approach not only fosters advanced predictive capabilities but significantly reduces uncertainties, addressing the evolving challenges encountered in modern semiconductor technologies.

Despite its innovative potential, the proposed method of integrating Adaptive Kriging into Semiconductor Reliability Analysis exhibits several limitations that warrant consideration. Firstly, the effectiveness of Adaptive Kriging is highly contingent upon the quality and quantity of the input data. If the data is sparse or lacks representativeness, the model may produce inaccurate predictions and may fail to capture existing complexities in failure mechanisms. Additionally, while Adaptive Kriging is adept at detecting areas of high uncertainty, it may struggle in high-dimensional spaces, where the curse of dimensionality could diminish the reliability of the prediction function. The underlying assumptions of stationarity in the Kriging process may not hold true in all scenarios, particularly if the behavior of failure mechanisms varies significantly across different operating conditions or over time. Furthermore, the incorporation of novel failure mechanisms like Hot Carrier Injection and Electrostatic Discharge requires precise parameter estimation, which can be challenging to achieve, potentially leading to an underestimation or overestimation of uncertainty bounds. Computational cost poses another limitation, as the iterative nature of Adaptive Kriging may render it less efficient in scenarios requiring real-time reliability assessments. Lastly, while the model provides a probabilistic approach, it does not automatically account for unforeseen factors such as manufacturing variability or changes in environmental conditions, which could significantly impact the reliability predictions. Therefore, while the integrated approach holds promise, careful validation and refinement are essential to mitigate these limitations in practical applications.

6. Conclusion

This paper introduces a novel methodology for Semiconductor Reliability Analysis via adaptive Kriging to address the limitations of current approaches in predicting semiconductor reliability accurately. The key innovation of this work lies in the application of adaptive Kriging, which dynamically adjusts model parameters based on the specific characteristics of the semiconductor device under analysis. By doing so, this methodology not only enhances the accuracy of reliability predictions but also offers a more efficient and robust framework for assessing semiconductor reliability. However, despite the promising results, there are limitations to be acknowledged. One potential limitation is the complexity involved in implementing the adaptive Kriging technique, which may require specialized expertise. In addition, the generalizability of this methodology to different types of semiconductor devices and operating conditions may also present challenges. For future work, further research could focus on optimizing the methodology for broader applicability and exploring additional techniques to enhance the adaptability and prediction accuracy of semiconductor reliability analysis. Moreover, conducting experimental validations and case studies would be imperative to validate the effectiveness and practicality of the proposed methodology in real-world scenarios.

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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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