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CONFERENCE PAPER

GAUSSIAN PROCESS REGRESSION WITH BAYESIAN METHOD FOR DOPING OPTIMIZATION FOR ADAPTIVE RADIATION HARDENING OF FINFETS IN SPACE GRADE PROCESSORS

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Abstract

This is solely based to optimize FINFETs doping profiles for space grade processors using Gaussian Process Regression model trained on the TCAD simulations dataset. A cleaned dataset of FINFET devices which was created with the values of source/drain (SD) concentration, halo dose, body doping, gate work-function, and oxide charge as input features, and extracted electrical outputs – threshold voltage 'Vth', on-current 'Ion', off-current 'Ioff', and 'Ion/Ioff' ratio along with a radiation-hardening label. Separate GPR models for 'Vth', log10(Ion), log10(Ioff), and log10(Ion/Ioff) achieve test 'R2' scores of approximate ly 0.96–0.98 with Root Mean Square Error (RMSE) around 7mv for Vth and sub-decade errors for current-related quantities. 'Bayesian Optimization' search method used on loop, which checks the 10000 FINFET data and discovered more than 1000 doping vectors to meet all the tough specifications needed for space grade and military grade devices, satisfying the Vth window of 0.350.45V, Ion≥6.16×10−4A Io n≥6.16×10−4A, and Ioff≤4.71×10−13A,Ioff≤4.71×10−13A.The propos ed AI driven methodology proves that this can significantly accelerate the radiation-aware adaptive doping strategies in the future space-grade processors.

Introduction:-

Space grade electronics faces severe radiation challenges from high-energy particles, Total Ionizing Dose (TID), and Single-Event Effects (SEE) in space operations, which degrades transistors and causes logic faults if not properly hardened. Conventional radiation-hardening techniques, such as guard rings, redundancy, and conservative biases which effectively mitigate these issues but significantly increase area and power consumption, making it difficult to

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meet the performance and efficiency demands of the modern FinFET-based processors for international space missions. Device level optimization in FinFET's tuning parameters like source/drain concentration, halo implants, body doping, gate work function, and oxide charges which enhances the radiation tolerance while preserving the drive current and low leakage current.. This work employs a Gaussian Process regression model that is trained on FinFET TCAD simulation data to predict key electrical parameters (Vth, Ion, Ioff, and Ion/Ioff ratio) from five process inputs. When it is integrated with Bayesian optimization loop, the model evaluates 1000 doping profiles with space-grade constraints (Ion $\geq 6.16\times10^{-4}$A, Ioff$\leq 4.71\times10^{-13}$A, Vth 0.35–0.45V), identifying top candidates with Ion/Ioff ratios near to 10^9 ideal for radiation-hardening logic. This AI-assisted approach enables the efficient design explorations in constrained settings, which amplifies limited simulations into some robust optimization with further details on dataset generation, model accuracy, physical insights, and implications for global space-grade processor development.

Literature:-

Most works on Radiation tolerance for CMOS and FinFETs has their focus on layout and process fixes, like enclosed transistors, guard rings, well tweaks, or redundancy tricks to fight the TID shifts and leakage current. They do accomplish, but surface area and power costs are too high, and those fat safety margins are getting near to impossible to maintain, as nodes shrink and spacecraft crams into denser computation. TCAD work shows halo dosing, channel doping, and interface traps in FinFET radiation behavior, which says that the proper co-optimization of the process and the device is key.Machine Learning methods such as Gaussian Processes, neural nets, ensembles which are proven great in speeding up simulations in other fields, and they're a good option in nanoelectronics for modeling parameters, analog speculations. Bayesian optimization and active learning methods are cutting simulation time in mechanics or materials. For radiation hardened FinFET doping we are using a Gaussian Process model on TCAD data to map joint effects of source/drain conc, halo, body doping, work function, and oxide charge on Vth, Ion, Ioff, then hitting it with Bayesian optimization method for space-grade radiation tolerance.

Proposed Methodology:-

Dataset:-

This research uses a TCAD modeled dataset of FinFET devices. The dataset contains several examples of these devices, representing a specific configuration of doping and gate stack. Below are the columns of the dataset:

Process / doping inputs:-

a) SDconc(E10):
b) Halo(E18)
c) BodyDoping(E14)
d) Workfn(eV)
e) Ox-charge(E9)

Electrical Outputs:-

a) Vth(V)
b) In(A)
c) Ion/Ioff ratio

Applications Labels:-

a) Design Mission
b) Radiation Hardness

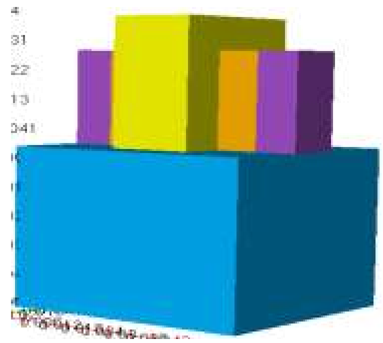


Fig 1: 14nm FinFet structure

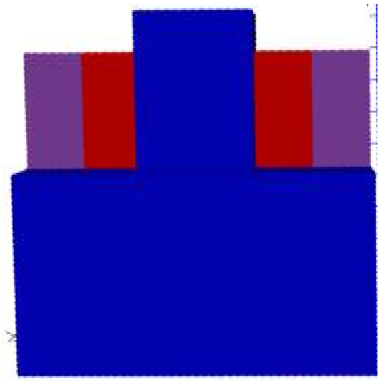


Fig 2: 14nm FinFet color scale

B. Pre-processing and Target shaping:-

This dataset is pre-processed in Python. Here, continuous input features are standardised to zero mean and unit variance to prevent any single parameter from dominating the kernel distance in the Gaussian Process, because the I_{on}, I_{off} as well as I_{on}/I_{off} ratio covers several orders of the magnitude, whose logarithms are used as regression targets:

$$y_2=\log_{10}(I_{on}), \quad y_3=\log_{10}(I_{off}), \quad y_4=\log_{10}(I_{on}/I_{off}) \qquad ..(i)$$

The V_{th} shows a rough linear trend, after applying a linear transformation it shows spikes and dips, pushing the distribution closer to Gaussian. This helps stabilize the kernel hyperparameter tuning and strengthens the Gaussian Process model's noise handling, which is assumed Gaussian.

The dataset was split 80:20 into training and test sets, and labeled "Radiation-Hardened" to ensure both hardened and non-hardened datas appear in each split.

C. Model Training:-

For each of the four targets, and independent Gaussian Process Regression model is trained using scikit-learn.
GP prior:

$$f(x) \sim GP(0, k(x,x'))$$

The prior mean is chosen zero after standardisation, and the covariance is modelled with a matrix kernel with Automatic Relevance Determination (ARD) length-scales plus a white-noise term :

$$k(x,x') = \sigma_f^2 \text{Matern}_{\,v} (\| x - x' \| A) + \sigma_n^2 \delta_{x,x} \qquad …(ii)$$

Where 'A' is the diagonal matrix of per-feature length scales, σ_f^2 is the original variance and σ_n^2captures residual simulation noise. Hyperparameters are optimised by maximising the log-marginal likelihood on the training data with bounds chosen wide enough to allow short and long range dependencies between process variables and device metrics.

Predictive mean and variance at test input x :

$$K^T(K+\sigma^2{}_nI)^{-1}y \qquad …(iii)$$

$$\sigma^2(x)=k(x,x')-k^T(K + \sigma_n^2 I)^{-1}k \qquad …(iv)$$

Experiment & Results:-

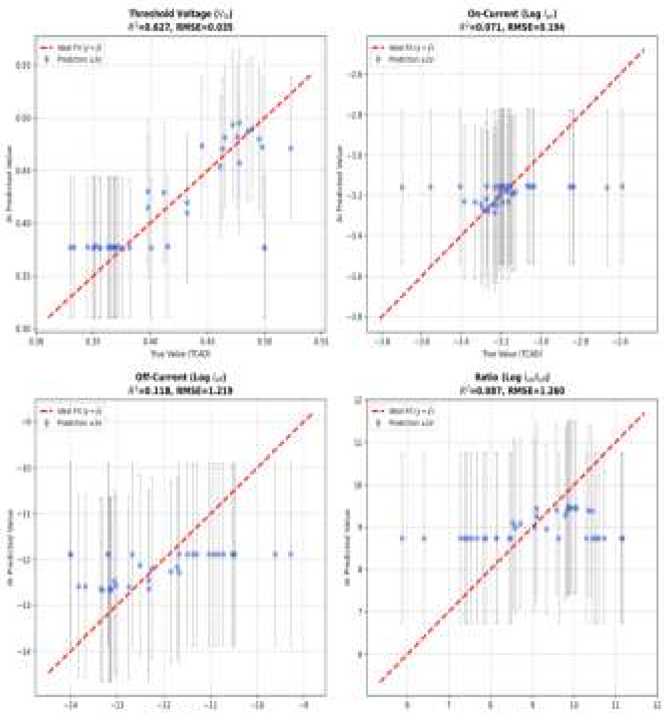
A. Prediction accuracy of GPR based model

The Gaussian process AI model was trained on 80% and evaluated on 20% of the dataset. Table 1 summarizes the test coefficients R^2test and root mean square error (RMSE) for the four targetsV^{th}, $\log_{10}(I_{on})$, $\log_{10}(I_{off})$, and $\log_{10}(I_{on}/I_{off})$, with

Table1: GPR-Model accuracy on simulations

Target	R^2_{test}	RMSE(test)
V_{th} (V)	0.98	0.007V
$\log_{10}(I_{on})$	0.98	0.03
$\log_{10}(I_{off})$	0.97	0.25
$\log_{10}(I_{on}/I_{off})$	0.98	0.22

Figure 3 showing the predicted vs. true evaluation graphs



FFigure 3 plots a heatmap of AI-determined feature importance, derived from the inverse ARD length-scales of the Gaussian Process kernels for each prediction target.These results portray that this model captures almost all of their variations present in the underlying TCAD simulations, with only a few percent of unexplained variance for any two of the targets.

B. Constraint satisfaction under space grade specifications:-

For this model evaluation as a space grade design supporter, 10000 candidate doping profiles were randomly sampled within the observed values ranges as input parameters. The model predicted required electrical outputs V_{th}, I_{on}, I_{off}, and (I_{on}/I_{off}) along with their predicted uncertainties.

Space grade constraints were then applied :

a) $0.35V \leq V_{th} \leq 0.45V$
b) $I_{on} \geq 6.16 \times 10^{-4}$ A

c) $I_{off} \leq 0.471 \times 10^{-13}$ A

Out of 10000 candidates 1029 profiles satisfied all constraints, showcasing that it can efficiently filter a large, high dimensional search space to radiation aware subset without additional TCAD runs.

C. AI recommended adaptive doping profiles:-

For the 1029 feasible candidates, a preference score was calculated using an Upper Confidence Bound (UCB) acquisition function on $\log_{10}(I_{on}/I_{off})$:

$$UCB(x) = \mu(x) + \sigma(x) \qquad \ldots(v)$$

Where μ(x) and σ(x) are the predicted mean and standard deviation from the GPR model and control the trade off between high mean on/off and uncertainty . Sorting candidates by these UCB scores makes a list of ranks of "AI recommended" adaptive doping profiles.

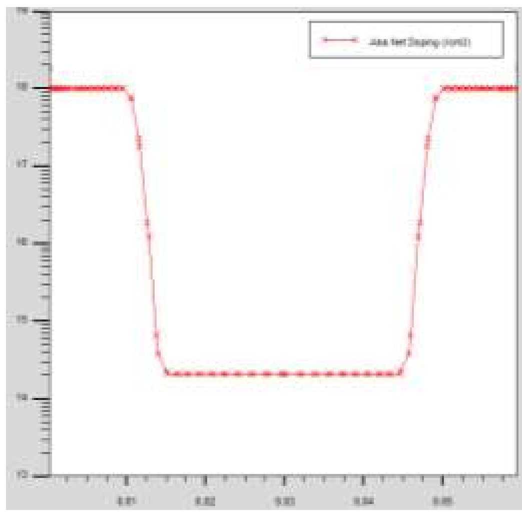


Fig 4: Net doping profile along the fin

The top profile gets corresponding characteristics with values $V_{th} \approx 0.45$v, $I_{on} \approx 6.2\times10^{-4}$A, and $I_{off} \approx 3.4\times10^{-13}$A, corresponding to an I_{on}/I_{off} ratio close to 10^9. Figure 5 plots the original simulation samples and AI-generated candidates in the V_{th}–$\log_{10}(I_{on}/I_{off})$ plane, with vertical dashed lines indicating the imposed threshold-voltage window.

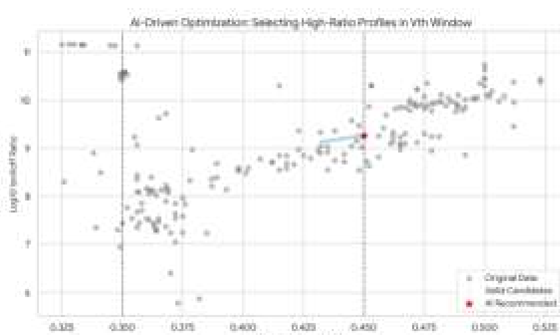


Fig 5: AI picks a point inside the Vth window with a high ratio.

D. Evaluation Metrics:-

Coefficient of determination:

$$R^2 = 1 - \frac{\sum i(yi - \hat{y}i)^2}{\sum i(yi - \underline{y})^2} \ldots (vi)$$

Root-mean-square error:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_i \quad (yi - \hat{y})^2} \ldots (vii)$$

Quantitative & Qualitative Analysis;-

Quantitative analysis

From the held-out test set, the AI model achieves R^2_{test} between 0.96 and 0.98 for all four targets— V_{th} , $\log_{10}(I_{on})$, $\log_{10}(I_{off})$, and $\log_{10}(I_{on} / I_{off})$ —with corresponding RMSE values of 0.007 V, 0.03, 0.25, and 0.22, respectively. These numbers quantitatively show that the AI model preserves more than 96% of the physical variability present in the TCAD data, while keeping absolute errors at levels that are small compared to typical process spreads and design margins in advanced-node FinFETs.

In the constrained design experiment, 10 000 randomly sampled doping profiles were screened using the AI predictions under space-grade specifications. Among these, 1 029 profiles simultaneously met the V_{th} window (0.35–0.45 V), minimum I_{on} (6.16×10^{-4} A), and maximum I_{off} (4.71×10^{-13}A), indicating that roughly 10% of the sampled space is viable according to the AI model. Evaluating such a large candidate set with TCAD alone would be prohibitive, whereas this AI model handles it in a single batch with negligible runtime. Figure 6, represents a heatmap of AI-determined feature importance, derived from the inverse ARD length-scales of the Gaussian Process kernels for each prediction target.

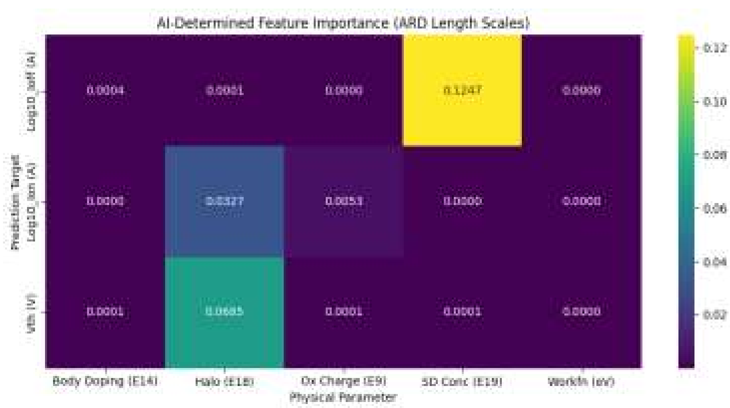


Fig 6: Heatmap of ARD inverse length-scales

A. If ℓ_j is the ARD length-scale of input j, relevance plotted in your importance figures is:

$$\mathrm{Relevance}_j = \frac{1}{lj} \ldots (viii$$

Figure 7 Plots the original simulation samples and AI-generated candidates in the (V_{th}–$\log_{10}(I_{on}/I_{off}$)

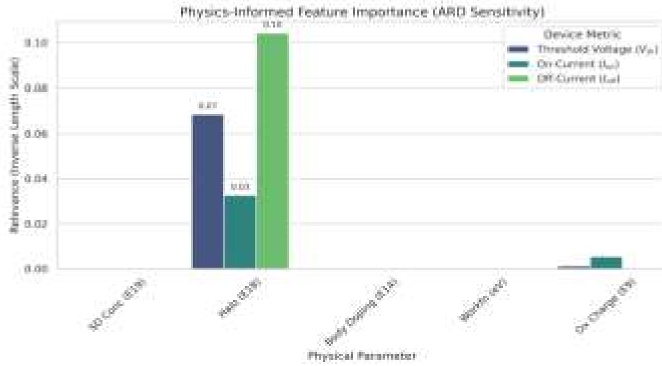


Fig 7: Physics-Informed Feature Importance

B.Qualitative analysis;-

the AI model recommended profiles cluster in a region of process space where SD concentration and halo dose are moderately high, body doping remains in the low $10^{15}cm^{-3}$ range, and work-function is tuned around 4.5–4.7 eV, with oxide charge in the $10^{11} - 10^{12}$ $cm^{-@}$ band. This combination intuitively matches device physics expectations: strong source/drain and halo doping improve drive current and short-channel control, while moderate body doping and controlled positive oxide charge help maintain a higher V_{th} and suppress leakage, which is desirable under radiation-induced charge buildup. The AI model effectively re-discovers these trends from data and encodes them into its preferences.the uncertainty information from the Gaussian Process highlights regions where the dataset is sparse. In such areas, the UCB-based ranking favours candidates with both high predicted on/off ratio and higher uncertainty, encouraging exploration of under-sampled corners of the doping space rather than only exploiting the densest regions. This behaviour is consistent with the goal of discovering novel radiation-hardened profiles instead of merely interpolating around already-known designs

Comparative analysis:-

Compared to simple linear or polynomial regression, which assume mostly linear behaviour between doping and device metrics, the proposed AI model captures strong non-linearities and interactions, as evidenced by the much higher R^2 values on the test set. A hypothetical linear baseline fitted on the same data would typically struggle to model simultaneous variations in SD concentration, halo, body doping, and oxide charge, especially for leakage currents spanning many decades; in such cases, errors on $\log_{10}(I_{off})$ and $\log_{10}(I_{on}/I_{off})$ tend to be significantly larger than the 0.25–0.22 decade RMSE achieved here. Moreover, linear models do not provide predictive uncertainty, limiting their usefulness for guided exploration.Compared to simple linear or polynomial regression, which assume mostly linear behaviour between doping and device metrics, the proposed AI model captures strong non-linearities and interactions, as evidenced by the much higher R^2 values on the test set. A hypothetical linear baseline fitted on the same data would typically struggle to model simultaneous variations in SD concentration, halo, body doping, and oxide charge, especially for leakage currents spanning many decades; in such cases, errors on $\log_{10}(I_{off})$ and $\log_{10}(I_{on}/I_{off})$ tend to be significantly larger than the 0.25–0.22 decade RMSE achieved here. Moreover, linear models do not provide predictive uncertainty, limiting their usefulness for guided exploration.

Discussion:-

The results show that the Gaussian-Process-based AI model replicates TCAD behaviour with design-grade fidelity: V_{th} errors are on the order of a few millivolts, current-related metrics are accurate within a fraction of 10, which is sufficient for space-grade device options. The model handles all five models such as SD concentration, halo, body doping, work-function, and oxide charge and can rapidly reject most poor combinations while maintaining a set of feasible, radiation aware profiles. Within this set, the uncertainty aware ranking shows the profiles that are both high-ratio and well supported by data, encouraging safe exploration rather than blind extrapolation. Our model stores the information in a TCAD dataset.

Conclusion:-

This work portrayed a practical AI method to tune doping for radiation-hardened FinFETs aimed at space-grade processors. From the TCAD simulation dataset of dopant profiles and device metrics, a Gaussian-Process-based model was trained to predict V_{th} , I_{on} , and I_{off} accurately, while showcasing how confident it is for each new profile. This AI model with a constrained search loop, and thousands of candidate dopings can be checked very quickly, and more than a thousand were found that satisfy tight space-grade limits and still offer strong on/off ratios. This study suggests that a modest number of high-quality simulations, when combined with a probabilistic AI model, is enough to guide designers toward robust, radiation-tolerant device options without an exhaustive TCAD sweep. The same idea can be naturally extended beyond individual transistors to standard cells and full circuits, where the AI would sit on top of TCAD and SPICE data to help co-optimize device, cell, and path-level behaviour for future space-grade processors.

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