Prediction of Single Event Upset-Induced Drain Peak Current Using Machine Learning

Sowon Kim[1], Geon Kim[1], Dongyeong Kim[1], Suyeon Kim[1], Jewon Park[1],
Shinwook Kim[1], Ryun Kang[1], Chaehyuk Lim[1], Hyeona Seo[1],
Jeonghyeon Yun[1], Juwon Lee[1], Hyerin Lee[1], Ujin Choi[2], Eojin Kim[2], Minwoo Jeong[2], and Myoungjin Lee[2,*]
[1]*Dept. of Intelligent Electronics and Computer Engineering, Chonnam National University, Gwangju, South Korea*
[2]*Dept. of Electronics and Computer Engineering, Chonnam National University, Gwangju, South Korea*

kjw333349049@gmail.com, rjsdlchd@gmail.com, gnodyoung@jnu.ac.kr, bollic4504@gmail.com, parkje0922@jnu.ac.kr
sinw1559@gmail.com, kang0228youn@jnu.ac.kr, dlacogur098@gmail.com, engine5kor@gmail.com, yunjunghyun0623@gmail.com
dlwndnjs2055@gmail.com, lhy2rin@gmail.com, cuj0528@naver.com, djwls1001@naver.com, blueminw07@naver.com, mjlee@jnu.ac.kr
[*]Corresponding author

***Abstract*—This study proposes a machine learning-based framework for predicting the drain peak current induced by a Single Event Upset (SEU) in a Buried Channel Array Transistor (BCAT) structure. Transient current responses were obtained through TCAD simulations under various radiation conditions, with linear energy transfer (LET) values ranging from 1 to 100 MeV·cm^2/mg and trap densities from 1×10^{13} to 1×10^{14} cm^{-3}. These data were used to train and validate a regression-based learning model capable of quantitatively estimating the drain peak current without additional physical simulations. The trained model achieved a determination coefficient (R^2) of 0.989 and a mean squared error (MSE) of 3.29×10^{-8}, demonstrating high predictive accuracy. The machine learning model successfully captured the nonlinear interactions between LET and trap density that govern SEU-induced transient behavior. This approach provides a computationally efficient surrogate to conventional TCAD analysis, enabling rapid evaluation of radiation-induced effects in advanced DRAM devices and offering practical insights for optimizing SEU-tolerant semiconductor design.**

***Index Terms*—DRAM, BCAT, SEU(Single Event Upset), LET(Linear Energy Transfer), Trap Density, Drain Total Current, Drain Peak Current**

I. Introduction

Dynamic Random Access Memory (DRAM) is a key component in modern computing systems due to its high integration density and fast operation. However, as semiconductor devices continue to scale down, DRAM becomes increasingly susceptible to radiation-induced effects, particularly under high-energy particle exposure such as space or high-altitude environments [1] [2] [3] [4]. Among these effects, Single Event Upset (SEU) caused by heavy-ion strikes has emerged as one of the most critical reliability concerns. When energetic ions penetrate the memory cell, they generate dense tracks of electron-hole pairs, inducing transient current spikes that may disturb or invert stored data [5]. To accurately analyze these radiation-induced transient phenomena, device-level simulation tools such as Technology Computer-Aided Design (TCAD) are commonly used. However, TCAD simulations are computationally expensive and time-consuming when considering multiple physical parameters such as Linear Energy Transfer (LET) and trap density. To address this limitation, this study proposes a machine learning-based framework that predicts the drain peak current induced by SEU in DRAM structures. By learning the nonlinear relationship between LET, trap characteristics, and transient current behavior, the proposed model enables fast and reliable estimation of SEU-induced current responses without extensive TCAD simulations.

II. Results and Discussion

A. Simulation Setup

This study used the Synopsys Sentaurus Technology Computer-Aided Design (TCAD) tool to design and simulate a 2-cell BCAT device. Fig. 1 illustrates the typical 2-Cell BCAT structure and the simulation setup for heavy-ion incidence [8]. In this setup, a storage node biased at 1.2 V is exposed to heavy-ion strikes, and the initial bias conditions are set to V_{DS} = 1.2 V and V_G = –0.2 V. When heavy ions penetrate the device, transient leakage currents are generated along the ion track, which temporarily disturb the normal operation of the memory cell.

Based on the simulation setup described above, a total of 80 transient TCAD simulation cases were generated by systematically varying LET and trap density. LET values were selected as 1, 5, 10, 20, 30, 40, 50, and 100 MeV·cm^2/mg, while trap densities ranged from 1×10^{13} to 1×10^{14} cm^{-3}. For each

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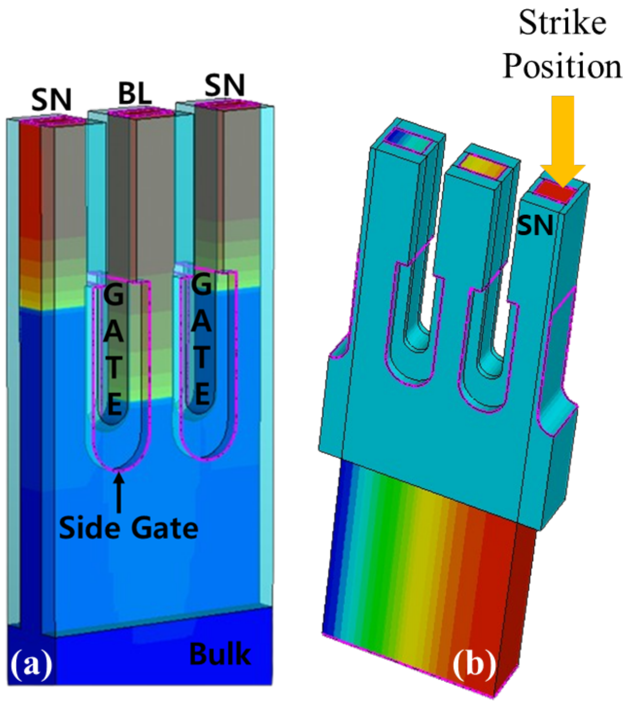

Fig. 1. (a) Typical 2-cell BCAT structure and (b) Simulation of heavy ion incidence

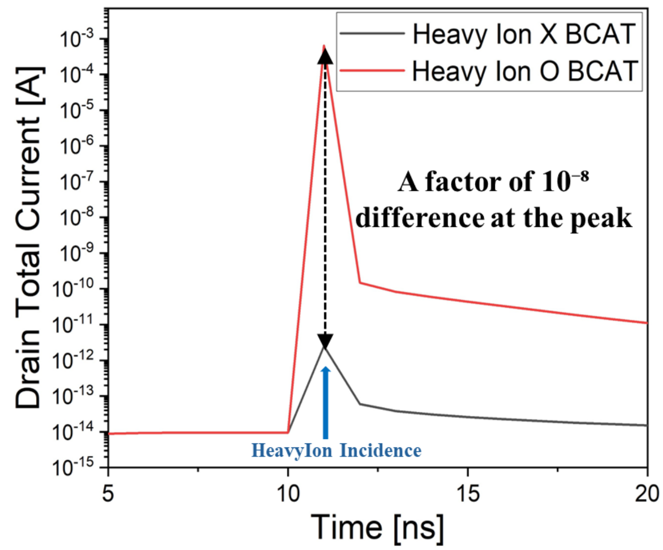

Fig. 2. Comparison of Drain Total Current with and without heavy ion incidence

condition, the transient drain current waveform was simulated and the drain peak current was extracted as the target output. This structured sampling strategy ensures uniform coverage of the parameter space while minimizing the computational cost of TCAD simulations.

B. Simulation Results and Analysis

The relationship between LET, trap density, and drain peak current is inherently nonlinear. LET determines the amount of charge deposited along the ion track, while trap density affects the transient drain current response. The combined influence of LET and trap density leads to a nonlinear dependence of the drain peak current on radiation energy and defect-related conditions.

Fig. 2 shows the transient drain current response when a heavy ion impacts the drain region at approximately 11 ns. When the heavy ion strikes the BCAT device, a large number of electron–hole pairs are generated along the ion track within the drain region. These charge carriers rapidly drift under the influence of the electric field, resulting in a sharp transient increase in the drain current, followed by a gradual decay as the transient response relaxes after the ion strike [6] [7]. This current waveform typically exhibits a narrow, high-amplitude spike corresponding to the initial charge deposition, and a subsequent tail as the transient disturbance diminishes. As the LET of the incident particle increases, the density of generated electron–hole pairs also increases, leading to a higher peak current and a stronger transient response. In addition, variations in trap density change the magnitude and temporal profile of the transient drain current. These trends indicate that the transient drain current is highly sensitive to both radiation energy and defect-related conditions. The rapid redistribution of charge carriers causes a temporary disturbance of the electric field distribution within the device, which can induce momentary malfunction or data instability [9]. Understanding this transient response is essential for evaluating SEU-induced behavior and forms the basis for constructing a machine learning model to predict the drain peak current under various radiation conditions.

Fig. 3 presents the correlation between the predicted and actual drain peak current values obtained from the Random Forest regression model trained on the TCAD dataset. Each data point represents a unique simulation case with different combinations of LET and trap density. The red diagonal line indicates the ideal 1:1 agreement between the machine learning prediction and the TCAD simulation, and most data points are closely aligned with this line. This strong correlation demonstrates that the trained model accurately reproduces the results of physics-based simulations across the entire data range.

The model achieved a coefficient of determination (R^2) of 0.989 and a mean squared error (MSE) of 3.29×10^{-8}, confirming its high predictive performance. This result indicates that the model successfully learned the nonlinear relationship between radiation energy deposition and defect-related conditions that govern the transient drain current behavior. In particular, the Random Forest algorithm effectively captured how increased LET leads to enhanced charge generation and larger current spikes, while higher trap density modifies the drain peak current response and the overall transient behavior.

Random Forest regression was selected due to its robustness in learning nonlinear relationships from relatively small datasets and its strong resistance to overfitting. A quantitative

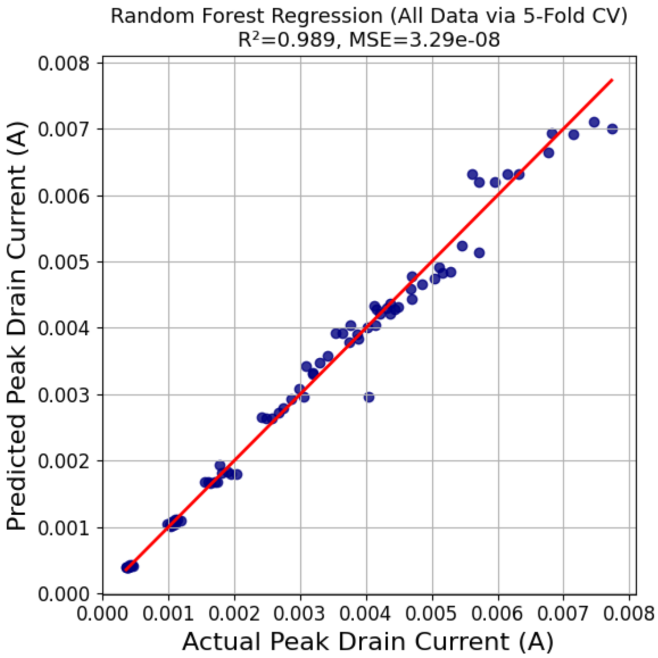

Fig. 3. Comparison between the predicted and actual drain peak current values obtained from the Random Forest regression model

comparison with linear regression and support vector regression is summarized in Table I.

In addition to its predictive accuracy, the proposed machine learning framework provides a substantial reduction in computational cost compared with conventional TCAD simulations. While a single transient TCAD simulation typically requires tens of minutes to hours depending on mesh resolution and physical models, the trained model can estimate the drain peak current within milliseconds for a given input condition. This corresponds to a reduction in computational time by several orders of magnitude, enabling efficient large-scale parameter exploration and reliability-aware design optimization for SEU-tolerant DRAM structures. These results demonstrate that data-driven modeling can serve as an effective and practical complement to physics-based device simulation for radiation effect analysis.

TABLE I
COMPARISON WITH OTHER REGRESSION MODELS

Model	R^2 (mean $\pm$ std)	MSE
Ridge (Linear)	0.8589 ± 0.0502	4.95×10^{-7}
SVR (RBF)	0.9725 ± 0.0256	9.85×10^{-8}
Random Forest	**0.989**	3.29×10^{-8}

Table I compares the performance of different regression models. Linear regression shows limited accuracy, indicating that the relationship between LET, trap density, and drain peak current is strongly nonlinear. SVR improves prediction accuracy but exhibits relatively large variance across cross-validation folds, suggesting sensitivity to data distribution. In contrast, Random Forest achieves the highest prediction accuracy with stable generalization performance, supporting its suitability for modeling SEU-induced drain peak current.

III. CONCLUSION

This study analyzed the drain peak current behavior induced by heavy-ion incidence in a BCAT structure and proposed a machine learning-based predictive framework. Using TCAD-generated data under various LET and trap density conditions, the model achieved high predictive performance with an R^2 of 0.989 and an MSE of 3.29×10^{-8}. The proposed framework enables rapid estimation of SEU-induced effects without additional TCAD simulations, serving as a reliable and computationally efficient surrogate tool for device-level radiation analysis. It should be noted that the proposed model is intended for interpolation within the trained LET and trap density ranges. Predictions outside these ranges may involve increased uncertainty and are not considered the primary use case of this framework. In practical DRAM design workflows, the surrogate model can be used to rapidly screen radiation and defect conditions prior to detailed TCAD simulations, thereby reducing the number of required simulation iterations. Future work will focus on extending the dataset and validating the approach using experimental radiation test data.

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