Soft Error Rate Estimation with TCAD and Machine Learning

Masanori Hashimoto Wang Liao Soichi Hirokawa
Department of Information Systems Engineering, Osaka University
{hasimoto, wang.liao}@ist.osaka-u.ac.jp

***Abstract*—We have proposed a neutron-induced soft error rate (SER) estimation method that incorporates machine learning with Monte Carlo radiation transport simulation. Multiple sensitive volumes based machine learning discriminator makes fast SER estimation possible for a unit circuit (e.g. SRAM cell) consisting of several transistors. The discriminator takes charges deposited by a secondary ion to individual volumes of all the transistors as input and outputs the discrimination result, i.e. upset or non-upset. Supervised learning with the training data obtained by TCAD simulations constructs the discriminator. This paper discusses the discriminator construction for 65-nm ultra-thin-box FD-SOI SRAM with TCAD. We experimentally demonstrate the multiple sensitive volumes assignment is useful for building a precise discriminator. We also discuss the critical volumes and transistors for discriminator performance.**

I. Introduction

Due to miniaturization and highly integrated VLSI, radiation effects become one of the serious problems on microelectronics devices. Especially in terrestrial environments, neutron-induced soft errors become one of primary reliability issues.

Various estimation methods that estimate neutron-induced soft error rate (SER) using Monte Carlo radiation transport simulation have been proposed (see [1]). To simplify the simulation model and save CPU time, most of them introduce sensitive volume method [2]. This method considers that the charge deposited in the sensitive volume by a secondary ion is collected to drain node. According to the amount of the collected charge, this method discriminates whether an SEU occurs or not.

Aiming at more accurate discrimination, K. M. Warren et al. introduced a multiple sensitive volumes method [3]. It calculates the total collected charge as the weighted sum of the charge deposited in each sensitive volume, where each weight represents the charge collection efficiency. W. Tianqi et al. point out the contribution of charge deposition to on-transistor and suggest to assign a sensitive volume to on-transistor in addition to off-transistor [4]. A problem of the conventional multiple sensitive volumes methods is that careful assignment of multiple sensitive volumes and characterization of the weights are necessary before the Monte Carlo radiation transport simulation, and sometimes those require empirical optimization. Also, those assignment and characterization depend on the supply voltage and body voltage, and hence the Monte Carlo simulation must be executed for each voltage configuration.

For facilitating the discriminator construction and improving its accuracy, we proposed to use machine learning technique in SER estimation in [5]. The proposed machine learning

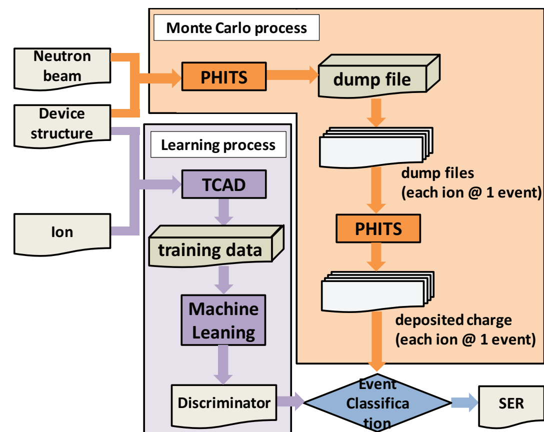

Fig. 1. SER estimation flow based on machine learning.

based method decouples the Monte Carlo radiation transport simulation and the event discrimination, and hence the same radiation transport simulation results can be reused for various discriminators corresponding to, for example, different voltage configurations. On the other hand, our previous work [5] did not show the advantage of finely discretized multiple sensitive volumes compared with other a single or fewer volumes. In this work, we compare the performances of the discriminators constructed with multiple sensitive volumes and fewer sensitive volumes using TCAD data for 65-nm SOTB (Silicon-on-Thin-Buried Oxide) SRAM, and demonstrate the superiority of the multiple sensitive volumes based discriminator, where SOTB is a kind of ultra-thin-box FD-SOI [6]. Also, we discuss the important volume using the discriminators constructed with different configurations.

II. Machine Learning Based Soft Error Discriminator

We briefly introduce the proposed discriminator construction and its usage in SER estimation [5]. Fig. 1 shows the flow of the machine learning based SER estimation. We can assign multiple sensitive volumes within a single transistor, and we can apply such an assignment to multiple transistors within a unit circuit (e.g. a SRAM cell). There are Monte Carlo process and learning process. Monte Carlo process executes Monte Carlo radiation transport simulation with the information on neutron beam and device structure. Monte Carlo simulator, e.g. PHITS (Particle and Heavy Ion Transport code System) in [7], outputs the dump file that contains information on many secondary ions. Subsequently, the information on each secondary ion in dump file is given to PHITS, and the

© 2017 The Japan Society of Applied Physics

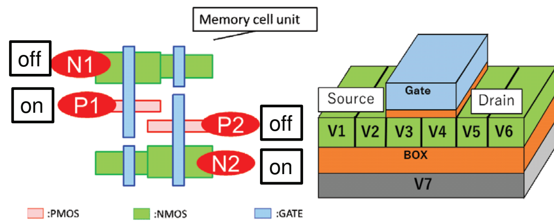

Fig. 2. SRAM memory cell unit constructed in TCAD and sensitive volume allocation in a single transistor. A latch in the cell consists of four transistors (N1, N2, P1, P2) composing two inverters. The values of charge deposited in the seven volumes of V1 to V7 of N1, N2, P1, and P2 are recorded for machine learning.

amounts of charge deposited in individual sensitive volumes are obtained.

For such a classification purpose, machine learning, more specifically, supervised machine learning, such as support vector machine and random forest, is suitable. In the learning part, to construct a discriminator for upset classification, we prepare a training data set of TCAD simulation results; ions are injected with various directions within a unit circuit, and we record whether an upset occurs or not and how much charge is deposited in each sensitive volume. Then, we construct a discriminator that tells us whether an upset occurs or not as a function of the amounts of charge deposited in the individual sensitive volumes and their sums. The influence of training data selection and sensitive volumes assignment on discriminator performance is discussed later in Section IV.

Once the discriminator is available, we can immediately judge whether an upset occurs or not for each event simulated in PHITS. By counting the number of upsets, we can obtain the SER. An advantage of the proposed method is that empirical adjustment of sensitive volumes is not necessary. Therefore, we do not need to change the sensitive volumes assignment for different voltage configurations.

III. Discriminator Construction for Upset Classification

A. Simulation Setup and Data Preparation

In the learning process, we prepared the training and test data using 3D TCAD simulator (Sentaurus of Synopsys). We constructed a 3D model of a SRAM cell consisting of six SOTB transistors shown in Fig. 2. This model has a 10-nm thick SOI layer and 12-nm thick BOX layer. The depth of the STI is 0.4 μm. We set seven sensitive volumes to each transistor; (V1/V2) the left/right half of source region under the gate, (V3/V4) the left/right half of SOI layer under the gate, (V5/V6) the left/right half of drain region under the gate, and (V7) the region under the BOX layer. An observation that the minimum LET for upset occurrence is much different even inside a transistor [8] motivates us to do such a fine volume allocation. The supply voltage was set to 0.3 V. The density of charge generation was assumed to follow a Gaussian distribution with a standard deviation of 30 nm [9]. We randomly injected ions whose LET was less than 100 pC/μm. The flight length of the ion was randomly determined, where the minimum flight length was 0.3 μm. For each simulation, we calculated the charge deposited in each sensitive volume and recorded the charge values and whether an upset occurred or not as a sample. We generated 5,389 samples for training

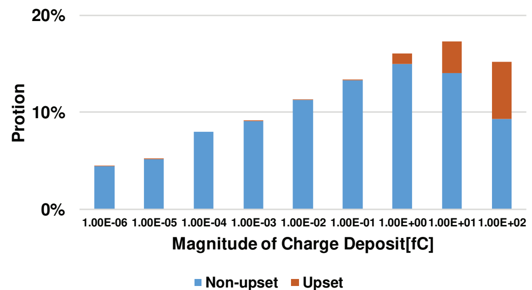

Fig. 3. Distribution of magnitude of deposited charge.

and test by TCAD simulation, where 562 samples among them are upset samples. The ratio of upset samples to non-upset ones is 0.116. Fig. 3 shows the proportion of ion samples in TCAD ranked by order of quantity of the total charge deposited into V1 to V7. As the total charge becomes small, the number of upset samples decreases.

B. Discriminator Construction and Evaluation

We chose random forest as a machine learning method since this algorithm works well even for non-linear classification problems and it can pick up the useful features, namely critical sensitive volumes in this case. Therefore, it requires less empirical construction and adjustment of sensitive volumes and, in this subsection, all the sensitive volumes are considered in the discriminator construction. More precisely, the amounts of charge deposited in V1 to V7 and their sums corresponding to adjacent volumes, such as V1+V2, V1+V2+V3+V4+V5+V6, are given to machine learning as features. We will show the advantage of multiple sensitive volumes by comparing it with different discriminators constructed with a single or fewer sensitive volumes in the next section.

We prepared training data sets, each of which consists of 300 upset and a certain number of non-upset samples randomly selected from the TCAD simulation results. The number of 300 for upset samples was determined so that the half of upset samples were left for test, while the number of non-upset samples ranged from 300 to 700 to clarify the importance of the balance between upset and non-upset samples. The sample balance is expected to influence the ability of discriminator to identify upsets. For each configuration of non-upset sample numbers, we generated 20 sets of training data randomly and constructed the discriminators.

The remaining 262 upset samples and about 3000 non-upset samples were used for the test of the trained discriminators. In the test, we have four types of classification results.

- TP (true positive): Both TCAD and classification results are upset.
- FN (false negative): TCAD result is upset, and classification result is non-upset.
- FP (false positive): TCAD result is non-upset, and classification result is upset.
- TN (true negative): Both TCAD and classification results are non-upset.

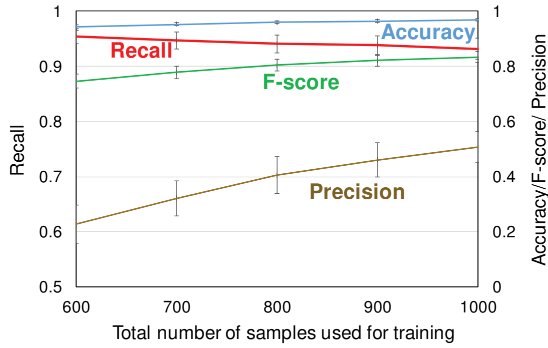

Fig. 4. Performance of discriminator with multiple sensitive volumes.

Four metrics of $accuracy$, $recall$, $precision$ and $F\text{-}score$ are defined to evaluate the performance of the discriminator.

$$accuracy = \frac{\#TP + \#TN}{N_{Test}}, \tag{1}$$

$$recall = \frac{\#TP}{\#TP + \#FN}, \tag{2}$$

$$precision = \frac{\#TP}{\#TP + \#FP}, \tag{3}$$

$$F\text{-}score = \frac{2 \times precision \times recall}{precision + recall}, \tag{4}$$

where N_{Test} is the number of samples used for the test.

Fig. 4 shows the performance of the discriminator constructed with multiple sensitive volumes of all the four transistors. The x-axis is the total number of training data, where larger training data means the number of non-upset samples increases since the number of upset samples is fixed to 300. As shown in the figure, $recall$ decreases from 95.8% to 93.4% as the number of non-upset samples increases in the training data set. This tendency is attributed to the same weight for all the samples used in training process, regardless of its label of upset or non-upset. On the other hand, $F\text{-}score$ and $accuracy$ increase from 73.2% and 93.9% to 82.4% and 96.5%, respectively, as the number of non-upset samples increases. Depending on the purpose, the appropriate sample balance may change. For overall SER estimation, $recall$ could be more important since a small number of upset samples must be found from the large quantity of non-upset ones. On the other hand, for MCU (multiple cells upset) analysis, for example, the precise classification for each event might be demanded.

IV. Discussion on Sensitive Volumes Assignment

This section compares the performance of the discriminators constructed with different sensitive volumes assignments. The same TCAD simulation results are used as either training data or test data for various discriminator constructions and evaluations, but some values of deposited charge are neglected according to the assignment of sensitive volumes. The numbers of upset and non-upset samples for training are both 300.

To make the explanation easier, we name sensitive volumes shown in left of Fig. 2 as follows; D (drain; V5 and V6), C (channel; V3 and V4), S (source; V1 and V2) and B (substrate; V7). The discriminator constructed in the previous section is called as DCSB. At the circuit level, four transistors composing a latch are also divided into on (N2 and P1), off (N1 and P2) and on&off (all the transistors) groups according to their initial states of TCAD simulation. We will discuss the selection of transistors in the last subsection whereas all the transistors are considered in the other subsections without additional explanation.

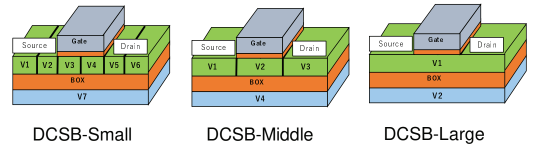

Fig. 5. Different configurations of sensitive volume size.

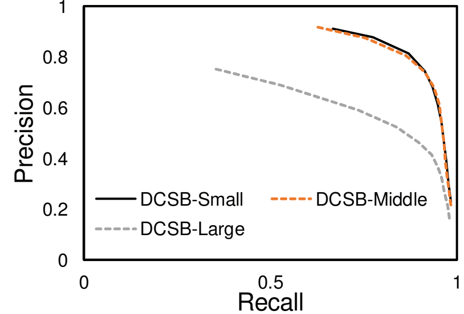

Fig. 6. Discriminator performance comparison w.r.t. sensitive volume size.

A. Sensitive Volume Size

We varied the size of sensitive volumes as shown in Fig. 5, and evaluated the discriminator performance. Fig. 6 shows the precision-recall (PR) curves corresponding to three size configurations of DCSB-small, DCSB-middle and DCSB-large. In the PR curve, the upper right represents better discriminator performance. For drawing the PR curves, we swept the threshold value of the constructed random forest discriminator from 0.05 to 0.95. We can see that DCSB-large has a much poorer performance compared to DCSB-small and DCSB-middle. Thus, multiple sensitive volumes based discriminator construction is important for accurate classification. On the other hand, the difference between DCSB-small and DCSB-middle is small. For SOTB transistors, further discretization beyond them for a larger number of sensitive volumes is not necessary.

B. Sensitive Volume Allocation

We next evaluate the importance of D, C, S, and B, separately. Fig. 7 shows the allocations of sensitive volumes. DCS, DCB, CSB, and DSB are constructed such that B, S, D or B is removed from DCSB, respectively. Fig. 8 shows the discriminator performances. The PR curve of DCSB is almost identical to that of DCS, which indicates the substrate B is not important for upset classification. Next, we compare DCB, CSB, and DSB to know which is the most important region for classification, source S, channel C or drain D. Fig. 8 shows that DCB has the poorest performance, which means source S is the most important. On the other hand, drain D is the least important. This result implies that the most sensitive region for upset, which is generally drain D, is not necessarily the most relevant for classification.

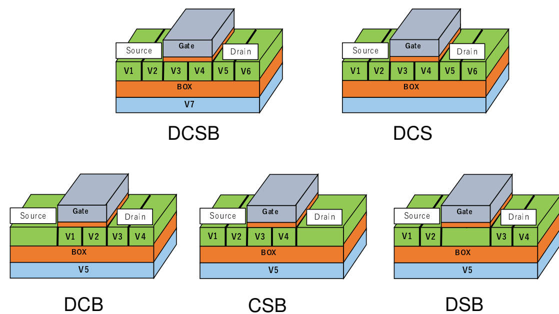

Fig. 7. Sensitive volumes assignments in DCSB, DCS, DCB, CSB and DSB.

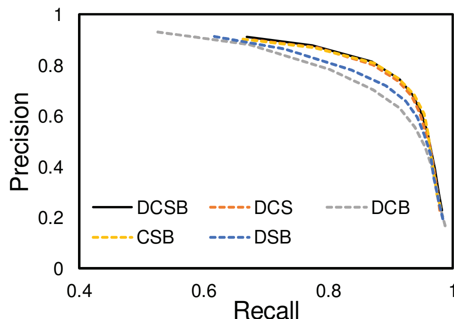

Fig. 8. Discriminator performance comparison among DCSB, DCS, DCB, CSB and DSB.

C. Transistor Selection

The subsections above considered all the four transistors in the latch. Here, we discuss which transistor is more important for upset classification. We first evaluate the importance of on transistor group. Fig. 9 shows the performance variation due to transistor selection. We can see off group is more important than on group for upset classification. While the discriminator constructed with off group is close to the one with on&off group in high recall region, the discriminator with on&off groups attains higher precision. Taking into account on transistors is helpful to improve the classification precision.

We next evaluate whether off NMOS (N1) or PMOS (P2) plays a more important role for classification. Fig. 10 shows the discriminator considering off PMOS has a better PR curve. This result indicates off PMOS is more important for classification whereas off NMOS is more sensitive in general in literature. Again, the most sensitive region is not necessarily the most critical for discriminator construction.

V. Conclusion

In this paper, we experimentally discussed the impact of sensitive volumes allocation on the performance of upset discrimination. Taking into account multiple sensitive volumes of all the transistors gives the better classification performance, as we expected. We also observed that the most sensitive volume is not necessarily the most important volume in the discriminator construction. In the future work, we will conduct the similar evaluation to bulk CMOS and FinFET SRAMs.

Acknowledgments

This work was partially done in "Ultra-Low Voltage Device Project" of LEAP funded and supported by METI and NEDO. The authors thank Dr. Shin-ichiro Abe of Japan Atomic Energy Agency, Prof. Jaehoon Yu of Osaka University and Prof. Yukinobu Watanabe of Kyushu University for their technical discussions.

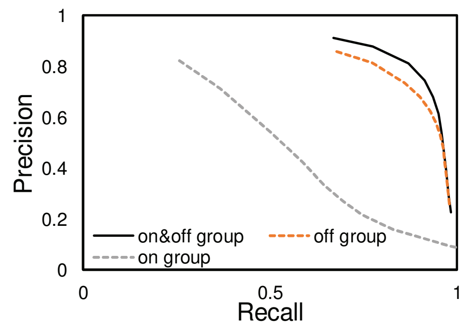

Fig. 9. Discriminator performance comparison w.r.t. off, on, and on&off transistor groups.

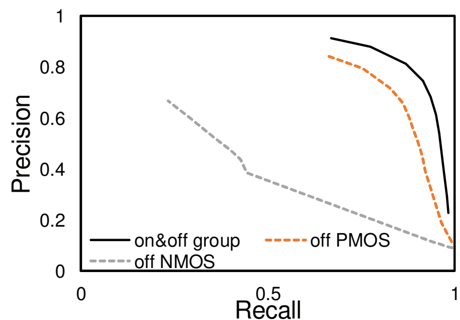

Fig. 10. Discriminator performance comparison w.r.t. off NMOS and off PMOS.

References

[1] R. A. Reed, et. al., "Anthology of the Development of Radiation Transport Tools as Applied to Single Event Effects," *IEEE Trans. Nuclear Science*, vol. 60, no. 3, pp. 1876–1911, June 2013.

[2] P. Roche, G. Gasiot, K. Forbes, V. O'Sullivan, and V. Ferlet, "Comparisons of Soft Error Rate for SRAMs in Commercial SOI and Bulk Below the 130-nm Technology Node," *IEEE Trans. Nuclear Science*, vol. 50, no. 6, pp. 2046–2054, Dec. 2003.

[3] K. M. Warren et al., "Monte-Carlo Based On-Orbit Single Event Upset Rate Prediction for a Radiation Hardened by Design Latch," *IEEE Trans. Nuclear Science*, vol. 54, no. 6, pp. 2419–2425, Dec. 2007.

[4] W. Tianqi et al., "Single-Event Upset Prediction in SRAMs Account for On-Transistor Sensitive Volume," *IEEE Trans. Nuclear Science*, vol. 62, no. 6, pp. 3207–3215, Dec. 2015.

[5] S. Hirokawa, R. Harada, K. Sakuta, Y. Watanabe, and M. Hashimoto, "Multiple Sensitive Volume Based Soft Error Rate Estimation with Machine Learning," *Proc. European Conference on Radiation and Its Effects on Components and Systems (RADECS)*, 2016.

[6] Y. Yamamoto, et al., "Ultralow-voltage operation of Silicon-on-Thin-BOX (SOTB) 2Mbit SRAM down to 0.37 V utilizing adaptive back bias," in *Dig. Symposium on VLSI Circuits*, pp. T212–T213, 2013.

[7] K. Niita, N. Matsuda, Y. Iwamoto, H. Iwase, T. Sato, H. Nakashima, Y. Sakamoto, and L. Sihver, PHITS: Particle and Heavy Ion Transport Code System, Version 2.23 JAEA-Data/Code. 2010-022, Japan Atomic Energy Agency, 2010.

[8] S. Hirokawa, R. Harada, M. Hashimoto and T. Onoye, "Characterizing alpha- and neutron-induced SEU and MCU on SOTB and bulk 0.4-V SRAMs," *IEEE Trans. Nuclear Science*, vol. 62, no. 2, pp. 420–427, Apr. 2015.

[9] S. Abe, Y. Watanabe, N. Shibano, N. Sano, H. Furuta, M. Tsutsui, T. Uemura, and T. Arakawa, "Multi-scale Monte Carlo simulation of soft errors using PHITS-HyENEXSS code system," *IEEE Trans. Nuclear Science*, vol. 59, no. 4, pp. 965–970, Aug. 2012.