Prediction of SET on SRAM Based on WOA-BP Neural Network

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Abstract

The incidence of high-energy particles into the semiconductor device would induce single event transients (SETs), which is a main threaten to MOS device. And the incidence distances and Linear Energy Transfers (LETs) have important effects on the SET current. A machine learning method based on Whale Optimization Algorithm-Back Propagation neural network (WOA-BPNN) model considering injection distances and LETs has been proposed to predict SET current in this paper. And this method could effectively reduce the simulation time from hours to seconds compared to device model. The current data that predicted by this method has been compared with the Technology Computer Aided Design (TCAD) simulation result which obtained in the background of the 40 nm process technology, the regression coefficient between the predicted value based on the proposed method and the TCAD simulation result was 99.76%, and the maximum integral relative error was 0.287% while the minimum integral relative error is 0.04%. Besides, the proposed method is also compared with PSO-BPNN (Particle Swarm Optimization, PSO) and GA-BPNN (Genetic Algorithm, GA), and the results demonstrated that the WOA-BPNN has prediction accuracy and timing saving advantages over the other two methods.

Keywords: Single event transients (SETs), Radiation effect, WOA-BP, Current, SRAM

1 Introduction

As Functional errors or permanent damage can be induced by the incidence of high-energy particles into a working device [1]. The SET is a significant problem related to the stability of MOS devices [2]. According to Moore's law, the reduction of the size of MOS devices will increase the sensitivity of transistors to radiation particles, and the SET is more harmful to devices [3-4]. Therefore, the research on SETs plays an important role in the security of devices.

Generally speaking, two main models, the device model and compact model, are employed to study SETs. The Technology Computer Aided Design (TCAD) software [5], a device toolkit provied by SYNOPSYS, has also been widely used to characterize the behavior of semiconductor devices of SET on different semiconductor technologies. Method based on TCAD simulation has high accuracy, but took a lot of time to obtain the current generated by the incident radiation particles [6-9]. In addition, in order to get the experiment results at different injection distances, it was necessary to repeat the simulation many times, which cost too much time. Thus, this method cannot be extended to large-scale circuits. Other researchers studied the influence of SETs by establishing the compact model which was composed of double exponential model and diffusion/collection model. The double exponential current model was inserted into the sensitive node of the target circuit to analyze the influence of SETs on the circuit [10-12]. Compact model plays an important role in the research of SETs and can be extended to large-scale circuits. Compared with device model, the simulation speed has been greatly improved. However, when the feature size of Integrated Circuit (IC) steps into the nanometer era, the accuracy of the classic double exponential model, which was proposed for sub-micron technology, becomes no more accurate as before. And Some parameters of the double exponential model, such as the total charge collected, rise time, and fall time were not easy to determine [13]. Rostand *et al.* proposed a SET current fault injection model based on incident position [11]. Based on the traditional double exponential model, two double exponential current sources were inserted into the sensitive nodes in parallel to study the single event effect through circuit level simulation. Although the model predicted well in medium circuits, but the parameters were affected by the recovery current of the logic unit. Rostand *et al.* proposed a compact model considering the bipolar amplification effect [14]. And this model was constrained by the underlying physical mechanism, which was complicated to implement. Therefore, a time-saving and simple model is needed to predict SET current.

In recent years, Artificial Intelligence (AI) has been widely studied in various fields, but there is little research on particle radiation. In 2020, Balakrishnan *et al*. used AI algorithms to predict and analyze the influence of SEU type soft errors in a given circuit [15]. The scheme could be used to predict SEU type faults in large-scale circuits. In 2021, the application of machine learning (ML) to automatically identify the SETs was proposed by Loveless *et al.*, which could use k-nearest neighbor (K-NN) to judge whether SETs exist or not, with an accuracy of 98% [16]. However, far too little attention has been paid to introduce machine learning to

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model SET current.

As an algorithm for signal forward propagation and error back propagation, BP neural network has been widely used in the data fitting field [17]. However, the BP neural network has the shortcomings of slow convergence and easy to fall into local optimum [18]. In order to address the above problems, meta-heuristic optimization algorithms were used to optimize the initial weight and threshold of BP neural network.

In this paper, a time-saving and simple model with acceptable accuracy for predicting SET current was presented. The transient current prediction model was based on WOA-BPNN, which used WOA to optimize the initial weight and threshold of the BP neural network. According to references [19-21], the incidence distances and LETs had an important effect on the SET current, and SET current changed with the incident distances and LETs. Therefore, the incident distances and LETs were used as the input of this model. In this model, TCAD simulation results were taken as samples to study the prediction of SET current. The experimental results demonstrated that this method was easy to implement and the simulation speed was greatly improved with an accepted accuracy. The method could effectively reduce the simulation time compared to device model and it is suitable when the process size of the integrated circuit reduced to nanoscale.

The structure of this article is as the following: Section II presents the algorithm flow chart of the proposed model, Section III introduces the model establishment and training process, Section IV displays the estimation result compared with TCAD simulations and other meta-heuristic optimization algorithms, like PSO-BPNN and GA-BPNN.

2 Algorithm Flow Chart

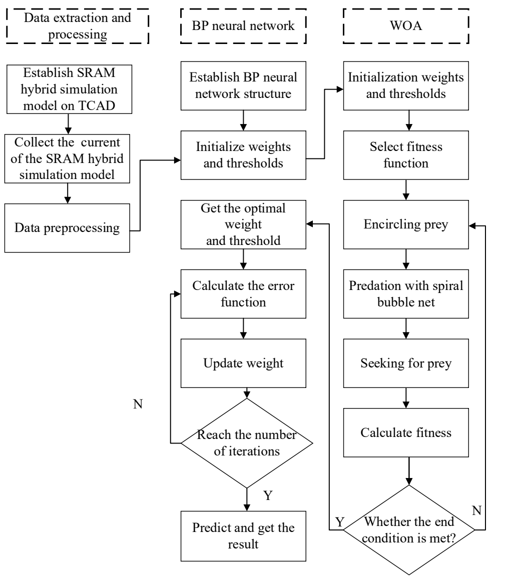


Figure 1. The algorithm flow chart of the WOA-BPNN

The algorithm flow chart of the WOA-BP neural network transient current prediction model is shown in Figure 1. The work was mainly comprised of three parts: data extraction and pre-processing, BP neural network and WOA. By adjusting the incident distances and LETs, the SET current, as training data, was obtained by the incidence of particles on the SRAM hybrid simulation model. The BP neural network was used to predict the current, and the WOA was used to optimize the initial weight and threshold of the BP neural network.

3 WOA-BP Current Prediction Model

3.1 Hybrid Simulation Model of SRAM

A 6 transistor SRAM hybrid simulation model was established on the TCAD platform under the background of the 40nm process to research the effect of LETs and distances on the SET current. The equipment structure is shown in Figure 2. The NMOS radiated by radiation particles used the three-dimensional NMOS device model, and other devices used the HSPICE (Simulation Program with Integrated Circuit Emphasis) model. NMOS devices were calibrated by adjusting a series of process parameters such as source-drain doping concentration, threshold voltage injection concentration and light doping leakage concentration to ensure the accuracy of NMOS model. Figure 3 exhibits the comparison of current-voltage characteristics at a working voltage of 1.100 V. It could be found that both are quite close and could be recommended for subsequent research.

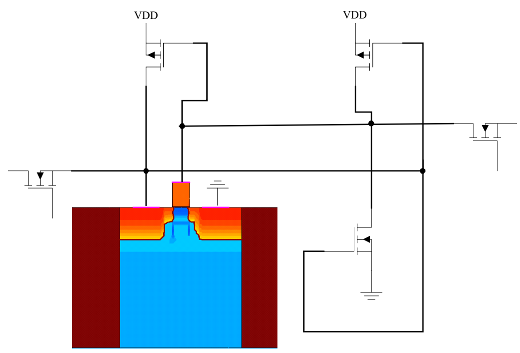
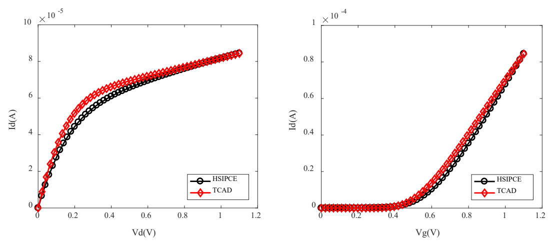


Figure 2. The equipment structure of SRAM



(a) I_d-V_d (b) I_d-V_g

Figure 3. Comparison of HSPICE and TCAD simulation electrical characteristic curves

On the basis of accurate three-dimensional device model, SET simulation analysis was performed by TCAD. Heavy ions vertically hit the NMOS transistor at different distances after 1 ns and the LET was 0.010 pC/μm. As shown in Figure 4, as the incident distance increased, the peak value of the SET current decreased. On the one hand, increased electron and hole combination results in reduced charge collection when the distance increases. On the other hand, the influence of the depletion region formed by the anti-biased PN junction between the drain and the well on the electron drift motion decreases with the increase of the distance, which also leads to less charge collection composed of charge drift motion.

As analysis above, LET and injection distance are two key parameters for SET analysis.

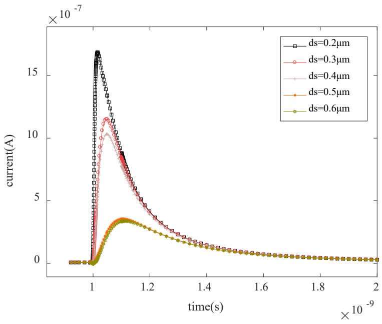


Figure 4. Transient current distribution at different distances when LET is 0.010pc/µm

3.2 BP Neural Network

As an algorithm for signal forward propagation and error back propagation, BP neural network has been widely used in the data fitting field.

By preprocessing the input variables, the learning speed and quality of the neural network could be speeded up. In order to reduce the dynamic range and improve the convergence rate, standardization to preprocess data was utilized in this work [17]. The standardized formula is as follows:

$$X_i = \frac{1}{\sigma_i}(x_i - \mu_i), \tag{1}$$

where X_i is the data after standardizing, x_i is the original value and μ_i is the mean value.

The training efficiency of BP neural network and the performance of this model are related with numbers of nodes in hidden layer. There is no definite rule to specify numbers of hidden layer nodes, which requires repeated experiments to get the best value. After a lot of training times, the BNPP parameters used in the proposed model were listed in Table 1. The numbers of nodes in the first hidden layer, the second hidden layer and in the third layer were 15, 10, and 8, respectively. The parameters of the BP neural network were as follows: the optimizer adopted Adam Optimizer, the loss function selected Mean Square Error (MSE), the learning rate set at 0.001, and the activation function selected ReLU. In this work, a five-layer BP neural network was established, with incident distances, time and LETs as the input of the BP neural network and drain current as the output. The structure of BP neural network is shown in Figure 5.

The loss function is as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2, \tag{2}$$

where n is the number of current data; y_i is the factual current data and $\hat{y}_i$ is the predicted current data.

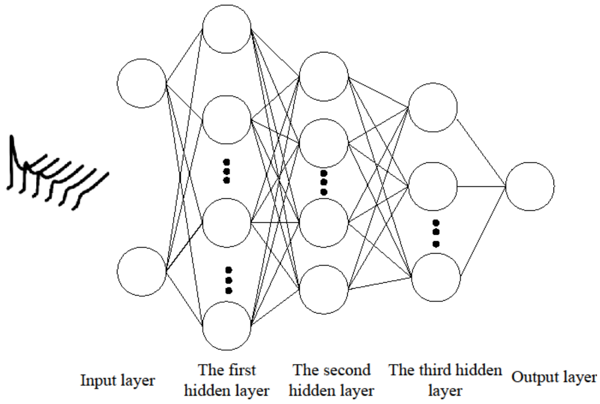


Figure 5. BP neural network structure

Table1. BPNN parameters

Input layer	3
Hidden layer	15-10-8
Optimizer	AdamOptimizer
Output layer	1
Learning rate	0.001
Iteration number	500
Activation function	ReLU
Input	LET, ds, time
Output	SET
Loss function	MSE (Mean Square Error)

3.3 The Application of WOA-BPNN on the Prediction of SET Current

As stated before, the BP neural network has the shortcomings of slow convergence and easy to fall into local optimum. In order to address the above problem, meta-heuristic optimization algorithms were used to optimize the initial weight and threshold of BP neural network. WOA are particle swarm optimization algorithms that imitate the social behavior of a group of animals to optimize the algorithm [22]. Compared with other optimization algorithms, WOA has the advantage of simple operations, fewer parameters, and easier implementation. The combination of WOA algorithm with BPNN can further improve model accuracy and avoid falling into local minimum.

WOA has three basic operators encircling prey, predation with spiral bubble net and seeking for prey [22-23]. The optimization processes of WOA were as follows:

- using MSE as the fitness value: (2)
- encircling prey: (3)-(6)
- predation with spiral bubble net: (7)-(8)
- seeking for prey: (9)

$$D = \left|CX^*(t) - X(t)\right|, \tag{3}$$

$$X(t+1) = X^*(t) - A \cdot D, \tag{4}$$

$$A = 2a \cdot r - a, \quad (5)$$

$$C = 2 \cdot r, \quad (6)$$

where t is the current iteration, X^* is the location of the optimal solution, X is the current location, a drops linearly from 2 to 0 during iteration, r is a random number between [0,1].

$$D' = \left| X^*(t) - X(t) \right|, \quad (7)$$

$$X(t+1) = \begin{cases} X^*(t) - A \cdot D & \text{if } p < 0.5 \\ D' \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t) & \text{if } p \geq 0.5 \end{cases}, \quad (8)$$

where b is a constant, l is a random number between [-1,1], p is a random number between [0,1].

$$\begin{cases} D = \left| C \cdot X_{\text{rand}}(t) - X(t) \right| \\ X(t+1) = X_{\text{rand}}(t) - A \cdot D \end{cases}, \quad (9)$$

where X_{rand} is the random location.

Table 2 shows the main procedure of the WOA algorithm with above equations.

It is easy to noted that the WOA optimization algorithm has a relatively simple structure, is easier to implement, and requires few parameters to be adjusted. The size of population and the number of iterations is needed to be given in advance. According to the definition the location of search agen $X_{i,j}$, where i is the population size, and j equals to the dimension of the problem. In the proposed WOA-BPNN, the dimension dim is the sum of the number of weights and thresholds which can be described as follow:

$$\begin{aligned} \dim = {} & in \times h1 + h1 + h1 \times h2 + h2 + \\ & h2 \times h3 + h3 + h3 \times out + out, \end{aligned} \quad (10)$$

where *in* and *out* are the numbers of nodes in the input layer and output layer, $h1$, $h2$ and $h3$ reprensent the numbers of nodes in the first, second and third hidden layers, respectively. Used the parameter settings in Table 1, the calculated value of dim is 317.

Based on the analysis above, a five-layer BP neural network was established, with time, distances and LETs as the input of the BP neural network and drain current as the output. And corresponding parameters was given in Table 1. A meta-heuristic optimization algorithm, WOA, was used to optimize the initial weight and threshold of BP neural network, which just needed to set size of population and the maximum number of iterations.

Table 2. Pseudocode of main WOA algorithm

```
Initialize the whale population Xi (i=1, 2, …, n)
Calculate the fitness of each search agent
X*= the best search agent
while(t< maximum number of iterations)
   for each search agent
   Updata a, A,C, l, and p
     if1(p<0.5)
       if2(|A|<1)
         Updata the position of current search agent by (4)
   else if2(|A| ≥ 1)
         select a random search agent ( X_rand )
         Updata the position of current search agent by (9)
       end if2
     elseif1 (p ≥ 0.5)
       Updata the position of current search agent by (8)
     end if1
   end for
check if any search agent goes beyond the search space
Calculate the fitness of each search agent
Updata X* if there is a better solution
end while
```

4 Analysis of Prediction Results

WOA-BP neural network model was built based on TensorFlow framework by the language of python in the windows system. The operating environment of this model was as follows: CPU was Intel Core i5-8500, GPU was NVIDIA GeForce GTX 1060 5GB, python3.6, TensorFlow-GPU 1.14.0. There were 200 simulation data with the distances between 0.200 μm and 0.8μm, LETs between 0.200 pc/μm and 1.03 pc/μm which were shown in Table 3 and Table 4.

Table 3. Distance of training and prediction data

	Distance (μm)			
0.2	0.225	0.250	0.275	0.300
0.325	0.350	0.375	0.400	0.425
0.450	0.475	0.500	0.525	0.550
0.575	0.600	0.625	0.650	0.675
0.700	0.725	0.750	0.775	0.800

Table 4. LET of training and number of prediction data

LET	0.2	0.4	0.5	0.6	0.7	0.8	0.9	1.03
num	25	25	25	25	25	25	25	25

In order to improve the generalization ability of the model and eliminate the correlation between data, the data was randomly selected as a training set and a test set at a ratio of 9:1. There were 200 TCAD simulation data, 180 of which were used for training and the remaining were used for testing.

To prove the effectiveness of the model, the predicted results were compared with the device simulation results. R^2 is a statistical index to measure the fitting effect. The larger R^2 is, the better the fitting effect is, indicating that the TCAD simulation results match the model prediction results better, which is defined as

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \overline{y}\right)^2}, \tag{11}$$

where y_i is the factual results, $\hat{y}_i$ is the predicted results, n is the number of current data, and $\overline{y}$ is the mean value.

In physics, the charge (Q) is obtained by integrating the current. When the charge accumulates to a certain threshold, the logic disorder of the device would happen. Therefore, the integration relative error ($E_{I,R}$) was introduced into the evaluation index to better measure the gap between the predicted value and the target value in charge accumulation, which is as follows:

$$E_{I,R} = \frac{|\hat{Q} - Q|}{Q}, \tag{12}$$

where Q is the factual integral results (the factual charge), $\hat{Q}$ is the predicted integral results (the predicted charge).

In order to demonstrate the performance of the proposed algorithm, two optimization algorithms were chosen for comparison. Similar to WOA, PSO is also a particle swarm optimization algorithm that imitate the social behavior of a group of animals to optimize the algorithm. In the meantime, a global optimization algorithm, GA, was also used for comparison. And, the integral relative error of charge ($E_{I,R}$), *MSE* and Regression coefficient (R^2) were taken as metrics of the model accuracy.

PSO-BPNN, GA-BPNN and WOA-BPNN were at the same population size and iteration number, which were 20 and 100, respectively. And the relevant parameter settings of BP neural network were consistent with Table 1 The performance of these three algorithms were listed in Table 5.

Table 5. The performance of the WOA-BP, PSO-BP and GA-BP

Indicators	WOA-BP	PSO-BP	GA-BP
MSE	0.0019	0.0021	0.0025
$E_{I,R}$ (min)	0.0004	0.0005	0.0008
$E_{I,R}$ (max)	0.0287	0.0445	0.0569
$E_{I,R}$ (mean)	0.0149	0.0193	0.0192
R^2	0.9976	0.9974	0.9973

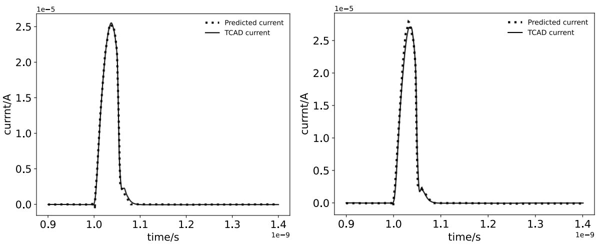
First of all, it could be seen from Table 5 that the Regression coefficients R^2 of three algorithms are all greater than 0.99. And the MSE obtained by WOA-BP was 0.0019, while the MSE obtained by PSO-BP and GA-BP were 0.0021 and 0.0025, respectively. Besides, three value of integral relative error of charge $E_{I,R}$ (min), $E_{I,R}$ mean and $E_{I,R}$ (max) values obtained by WOA-BP algorithm were all smaller than those of the GA-BP and PSO-BP algorithm.

By comparing R^2 and *MSE*, WOA-BPNN has advantages over other algorithms. Taking into account the above factors, we may draw the conclusion that the accuracy of WOA-BPNN is higher than others.

The training and prediction time were also given for evaluation in Table 6. It was found that the training time of WOA-BP algorithm and GA-BP algorithm were much shorter than that of PSO-BP algorithm, while the difference between WOA-BP algorithm and GA-BP algorithm was small. It should be noted that the training time consists of the optimization time of the optimization algorithm and the training time of the BP algorithm. Although the training time of different models is different, the prediction time is not very different, about 0.3s.

Table 6. The time consumption of the WOA-BP, PSO-BP and GA-BP

Indicators	WOA-BP	PSO-BP	GA-BP
Training time (h)	2.64	20.63	2.66
Prediction time (s)	0.3	0.28	0.33



(a) Best case (b) Worst case

Figure 6. Three-dimensional prediction results

Figure 6 showed the comparison between the SET current prediction of the WOA-BP neural network and the SET current of the TCAD simulation results, where the best case was on the left and the worst case was on the right. The incidence distance corresponding to the worst case is 0.20 μm, the LET is 0.95 pc/μm, and the integral relative error $E_{I,R}$ is the largest. The incident distance corresponding to the best case is 0.24 μm, the LET is 0.8 pc/μm, and the integral relative error $E_{I,R}$ is the smallest.

5 Conclusion

In this work, WOA-BP neural network has been proposed to predict SET current under different incident distances and LETs. According to the experiment and data analysis, the training time of the WOA-BP model was 2.64 hours, and the prediction time was 0.3 second, while the simulation time of TCAD was 8 hours. The time consumption was reduced from hours to seconds. Compared with device model, the prediction speed of the proposed method is greatly improved and time consumption by this method is reduced from hours to seconds with accuracy higher than 99%. Compared with device and compact model, the method proposed in this paper is simpler and easier to implement with acceptable accuracy without considering the complex internal physical mechanism.

Compared with other meta-heuristic optimization algorithms, the optimization time of this model was shorter than that of PSO-BPNN and GA-BPNN. Average relative error of charges could reach 0.0149.

At the same time, there still have some problems that this method needs to be further improved in fitting the peak value. For example, increase more training set data or further improve WOA performance is considered to improve the performance of WOA-BPNN.

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References

[1] T. Lange, M. Glorieux, D. Alexandrescu, L. Sterpone, Functional Failure Rate Due to Single-Event Transients in Clock Distribution Networks, *2019 14th International Conference on Design & Technology of Integrated Systems in Nanoscale Era (DTIS)*, Mykonos, Greece, 2019, pp. 1-6.

[2] N. Rostand, S. Martinie, J. Lacord, O. Rozeau, J. Barbe, G. Hubert, Single Event Transient in Bulk MOSFETs: Original Modelling for SPICE Application, *2017 International Conference on Simulation of Semiconductor Processes and Devices (SISPAD)*, Kamakura, Japan, 2017, pp. 89-92.

[3] I. S. Esqueda, H. J. Barnaby, M. P. King, Compact Modeling of Total Ionizing Dose and Aging Effects in MOS Technologies, *IEEE Transactions on Nuclear Science*, Vol. 62, No. 4, pp. 1501-1515, August, 2015.

[4] E. Garcia-Moreno, E. Isern, M. Roca, R. Picos, J. Font, J. Cesari, A. Pineda, Temperature Compensated Floating Gate MOS Radiation Sensor with Current Output, *IEEE Transactions on Nuclear Science*, Vol. 60, No. 5, pp. 4026-4030, October, 2013.

[5] Synopsys, Synopsys Sentaurus TCAD tools, [Online]. Available: https://www.synopsys.com/silicon/tcad.html.

[6] L. Artola, G. Hubert, S. Duzellier, F. Bezerra, Collected Charge Analysis for A New Transient Model by TCAD Simulation in 90 nm Technology, *IEEE Transactions on Nuclear Science*, Vol. 57, No. 4, pp. 1869-1875, August, 2010.

[7] J. Kim, J. Lee, J. Han, M. Meyyappan, Single-Event Transient in FinFETs and Nanosheet FETs, *IEEE Electron Device Letters*, Vol. 39, No. 12, pp. 1840-1843, December, 2018.

[8] S. Das, V. Kumari, K. Sehra, M. Gupta, M. Saxena, TCAD Based Investigation of Single Event Transient Effect in Double Channel AlGaN/GaN HEMT, *IEEE Transactions on Device and Materials Reliability*, Vol. 21, No. 3, pp. 416-423, September, 2021.

[9] Z. E. Fleetwood, N. E. Lourenco, A. Ildefonso, J. H. Warner, M. T. Wachter, J. M. Hales, G. N. Tzintzarov, N. J.-H. Roche, A. Khachatrian, S. P. Buchner, D. McMorrow, P. Paki, J. D. Cressler, Using TCAD Modeling to Compare Heavy-Ion and Laser-Induced Single Event Transients in SiGe HBTs, *IEEE Transactions on Nuclear Science*, Vol. 64, No. 1, pp. 398-405, January, 2017.

[10] L. Ding, W. Chen, T. Wang, R. Chen, Y. Luo, F. Zhang, X. Pan, H. Sun, L. Chen, Modeling the Dependence of Single-event Transients on Strike Location for Circuit-level Simulation, *IEEE Transactions on Nuclear Science*, Vol. 66, No. 6, pp. 866-874, June, 2019.

[11] N. Rostand, D. Lambert, Unified SPICE Model for Transient Ionizing Radiation Response of SOI MOSFET, *2021 International Conference on Simulation of Semiconductor Processes and Devices (SISPAD)*, Dallas, TX, USA, 2021, pp. 272-275.

[12] J. S. Kauppila, D. R. Ball, J. A. Maharrey, R. C. Harrington, T. D. Haeffner, A. L. Sternberg, M. L. Alles, L. W. Massengill, A Bias-Dependent Single-Event-Enabled Compact Model for Bulk FinFET Technologies, *IEEE Transactions on Nuclear Science*, Vol. 66, No. 3, pp. 635-642, March, 2019.

[13] F. Wrobel, L. Dilillo, A. D. Touboul, F. Saigné, Comparison of the Transient Current Shapes Obtained with the Diffusion Model and the Double Exponential Law-Impact on the SER, *2013 14th European Conference on Radiation and Its Effects on Components and Systems (RADECS)*, Oxford, UK, 2013, pp. 1-4.

[14] N. Rostand, S. Martinie, J. Lacord, O. Rozeau, T. Poiroux, G. Hubert, Single Event Transient Compact Model for FDSOI MOSFETs Taking Bipolar Amplification and Circuit Level Arbitrary Generation into Account, *2019 International Conference on Simulation of Semiconductor Processes and Devices (SISPAD)*, Udine, Italy, 2019, pp. 1-4.

[15] A. Balakrishnan, T. Lange, M. Glorieux, D. Alexandrescu, M. Jenihhin, Composing Graph Theory and Deep Neural Networks to Evaluate SEU Type Soft Error Effects, *2020 9th Mediterranean Conference on Embedded Computing (MECO)*, Budva, Montenegro, 2020, pp. 1-5.

[16] T. D. Loveless, D. R. Reising, J. C. Cancelleri, L. W. Massengill, D. McMorrow, Analysis of Single-Event Transients (SETs) Using Machine Learning (ML) and Ionizing Radiation Effects Spectroscopy (IRES), *IEEE Transactions on Nuclear Science*, Vol. 68, No. 8, pp. 1600-1606, August, 2021.

[17] J. Di, Investigation on the Traffic Flow Based on Wireless Sensor Network Technologies Combined with FA-BPNN Models, *Journal of Internet Technology*, Vol. 20, No. 2, pp. 589-597, March, 2019.

[18] H. Dong, X. Yang, A. Li, A Novel Method for Power Transformer Fault Diagnosis based on Bat-BP Algorithm, *2018 International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC)*, Xi'an, China, 2018, pp. 566-569.

[19] T. Makino, D. Kobayashi, K. Hirose, Y. Yanagawa,

H. Saito, H. Ikeda, D. Takahashi, S. Ishii, M. Kusano, S. Onoda, T. Hirao, T. Ohshima, LET Dependence of Single Event Transient Pulse-Widths in SOI Logic Cell, *IEEE Transactions on Nuclear Science*, Vol. 56, No. 1, pp. 202-207, February, 2009.

[20] Y. M. Aneesh, S. R. Sriram, K. R. Pasupathy, B. Bindu, An Analytical Model of Single-Event Transients in Double-Gate MOSFET for Circuit Simulation, *IEEE Transactions on Electron Devices*, Vol. 66, No. 9, pp. 3710-3717, September, 2019.

[21] C.-Q. Xu, Y. Liu, X.-D. Weng, Z.-B. Li, Y.-T. Yang, Single Event Transient Pulses Fault Injection Model based on LET for Circuit-Level Simulation, 2*020 IEEE 15th International Conference on Solid-State & Integrated Circuit Technology (ICSICT)*, Kunming, China, 2020, pp. 1-3.

[22] S. Mirjalili, A. Lewis, The Whale Optimization Algorithm, *Advances in engineering software*, Vol. 95, pp. 51-67, May, 2016.

[23] R. Sharma, V. Vashisht, U. Singh, WOATCA: A Secure and Energy Aware Scheme Based on Whale Optimisation in Clustered Wireless Sensor Networks, *IET Communications*, Vol. 14, No. 8, pp. 1199-1208, May, 2020.

Biographies

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