Prediction of Dynamic Random Access Memory Leakage Current Based Artificial Intelligence Model

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***Abstract*—Accurate prediction of leakage current is essential for realizing high-performance Dynamic Random Access Memory(DRAM). However, conventional Technology Computer-Aided Design(TCAD) simulations involve complex computations, resulting in high time and cost consumption. To overcome these limitations, this study developed a DRAM leakage current prediction model based on an Artificial Intelligence model, a Machine Learning model. TCAD simulation results were employed as training data, and three learning algorithms Broyden–Fletcher–Goldfarb–Shanno(BFGS), Adam optimizer and linear regression—were evaluated. Among them, the linear regression model demonstrated the best performance in predicting DRAM leakage current.**

***Index Terms*—Dynamic Random Access Memory(DRAM), Leakage current, Machnie Learning, Broyden–Fletcher–Goldfarb–Shanno(BFGS) model, Adam model, Linear Regression**

I. Introduction

With the advancement of Artificial Intelligence(AI) technologies, the demand for high-performance Dynamic Random Access Memory(DRAM) capable of processing massive amounts of data in processing units at high speed has been increasing. In particular, modern computing platforms such as data centers, high-performance computing systems, and AI accelerators require DRAM with high bandwidth and power efficiency to process a large amount of data. However, as device scaling continues, leakage current in DRAM cells has become a critical issue, degrading data reliability and device performance[1]. Because leakage current directly reduces DRAM's charge retention capacity storage node, thereby increasing frequency of refresh operation and increasing power consumption of device. Therefore, achieving high-performance DRAM requires accurate prediction and reduction of leakage current in cell transistors.

Traditionally, both academic and industrial approaches have relied on Technology Computer-Aided Design(TCAD) simulations to calculate the leakage current of DRAM cell transistors. TCAD serves as an electrical and physical simulator that calculates leakage current by solving carrier continuity equations. In addition, TCAD typically couples these equations with Poisson's equation and relevant transport models to capture device electrostatics and carrier dynamics, enabling detailed analysis of leakage mechanisms. However, such simulations demand extensive computational resources and time[2]. Consequently, these increased computational resource requirements and prolonged simulation times can impose constraints on semiconductor device development.

To overcome these limitations, this study develops a leakage current prediction model for DRAM cell transistors using machine learning, an artificial intelligence-based approach. The proposed framework aims to provide a model that can reduce the cost of simulations. The machine learning framework incorporates the Broyden–Fletcher–Goldfarb–Shanno(BFGS) algorithm considering data characteristic, the Adam optimizer, and a linear regression model. These methods were selected to examine both optimization-driven learning behavior(BFGS and Adam) and a simple yet strong baseline model(linear regression) for a low-dimensional prediction task. The performance of these three models is compared to identify the most suitable approach for accurate leakage current prediction, using quantitative metrics such as mean squared error and the coefficient of determination.

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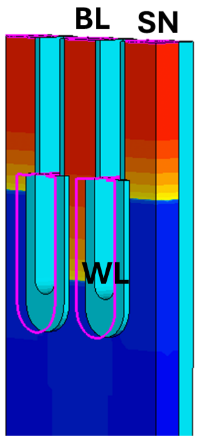

Fig. 1. Buried-Channel-Array Transisotr structure used in the simulation

TABLE I
DEVICE PARAMETERS

Parameter	Value
Gate Oxide Thickness	4nm
Gate Depth	80nm
Recessed Depth	150nm
L_g	18nm
W_{fin}	18nm
H_{fin}	18nm
Buried Insulator Thickness	40nm
Silicon Film Thickness	60nm
L_{in}	6nm
Metal Gate Work Function	4.6eV
N-type Peak Doping Concentration	$1 \times 10^{20}\text{cm}^{-3}$
P-type Peak Doping Concentration	$5 \times 10^{17}\text{cm}^{-3}$
Temperature	300K

II. Simulation Setup and Data Preparation

In this study, the prediction model was trained using leakage current data obtained from TCAD simulations provided by Synopsys[3]. Figure 1 illustrates the structure of the Buried-Channel-Array Transistor(BCAT), which serves as the DRAM cell transistor in the simulation. A two-cell BCAT structure of a 6F^2 DRAM was adopted, while only one cell was used for the simulation. Table 1 lists the datails of device paramters of BCAT in the simulation.

TABLE II
DATASET

Parameter	Value
Input Data	WL voltage
Output Data	SN leakage current
WL Voltage	0.0 $\sim$ -0.5V
WL Voltage step size	0.5mV
The number of train data	250
The number of test data	750

Table 2 lists the details of datasets. The training dataset for the leakage current prediction model uses the Word Line(WL) voltage as the input and the leakage current of the Storage Node(SN) corresponding to each WL voltage as the output. The WL voltage range was set between 0V and –0.5V, which corresponds to the leakage current measurement range. A step size of 0.5mV was applied, resulting in a total of 1,000 data points used for model training. The total simulation time was approximately eight hours, during which 250 data points were allocated for training and the remaining 750 for testing.

The prediction model was implemented as a Multi-Layer Perceptron(MLP) consisting of four hidden layers, each containing 32 neurons. Model performance was evaluated using two accuracy indicators: the Mean Squared Error(MSE) and the coefficient of determination(R^2).

III. Machnie Learning Model

A. BFGS model

The calculation of leakage current using TCAD requires a significant amount of time, which limits the number of data samples available for training the prediction model. Therefore, the Broyden–Fletcher–Goldfarb–Shanno(BFGS) algorithm is selected as it is well suited for modeling with a limited dataset[4]. BFGS is a quasi-Newton optimization method that approximates the Hessian(second-order curvature) of the objective function using gradient information, enabling stable and fast convergence without explicitly computing the true Hessian. Compared with purely first-order methods, this curvature-aware update can reduce the number of iterations required to reach a good solution, which is advantageous when the training dataset is small and repeated TCAD-based data generation is expensive.

TABLE III
PERFORMANC PARAMETER OF BFGS MODEL

	Training Data	Test Data
MSE	2.31×10^{-9}	2.32×10^{-9}
R^2	-4.33×10^{18}	-4.34×10^{18}

Table 3 presents the performance metrics of the BFGS model. As shown in the table, the Mean Squared Error(MSE) is relatively low, whereas the R^2 has a negative value. This indicates that the BFGS model fails to accurately predict the leakage current and, therefore, is not suitable for leakage current prediction. Specifically, although the low MSE implies that the model can reduce the average squared error on the evaluated samples, the negative R^2 means that the model performs worse than a naive baseline that simply predicts the mean leakage current value. This inconsistency suggests that the BFGS-optimized model does not capture the overall variance/trend of the leakage current data and generalizes poorly, likely due to the limited training data and the mismatch between the model complexity/optimization behavior and the underlying low-dimensional relationship. Consequently, the BFGS model is not considered appropriate for accurate leakage current prediction in this study.

B. Adam model

TABLE IV
PERFORMANC PARAMETER OF ADAM MODEL

	Training Data	Test Data
MSE	5.71×10^{-28}	5.72×10^{-28}
R^2	-2.58×10^{-4}	-2.59×10^{-4}

Table 4 presents the performance metrics of the Adam model, which is commonly used in neural network(NN) architectures. The absolute values of the MSE and the R^2 are lower compared to those of the BFGS model. However, since the R^2 value remains negative, the Adam model is also deemed unsuitable for leakage current prediction. Adam(Adaptive Moment Estimation) is a first-order stochastic gradient-based optimizer that updates network parameters using exponentially decaying estimates of the first and second moments of the gradients, which generally provides robust and fast training for deep networks under noisy gradients and large-scale datasets. In this study, however, the dataset is relatively small and the input–output relationship is low-dimensional, so the NN trained with Adam can be prone to unstable convergence and/or overfitting, leading to poor generalization on the test set and a negative.

C. Linear Regression model

TABLE V
PERFORMANCE PARAMETER OF LINEAR REGRESSION MODEL

	Training Data	Test Data
MSE	2.63×10^{-29}	2.66×10^{-29}
R^2	0.95	0.95

Figures 2 and 3 show the WL–leakage current graphs comparing the linear regression model prediction results with the 250 TCAD simulation training data and the 750 TCAD simulation test data, respectively.

and 3 show the WL–leakage current graphs comparing the prediction results of the linear regression model with the TCAD simulation data. Table 3 presents the performance metrics of the linear regression model, where the R^2 is close to 1. This indicates that the linear regression model is the most suitable for predicting leakage current. Linear regression is a simple yet effective supervised learning method that models the output as a linear function of the input by estimating coefficients that minimize the squared prediction error. Because the leakage current in this study exhibits an approximately monotonic and near-linear dependence on the WL voltage over the investigated range, the linear model can

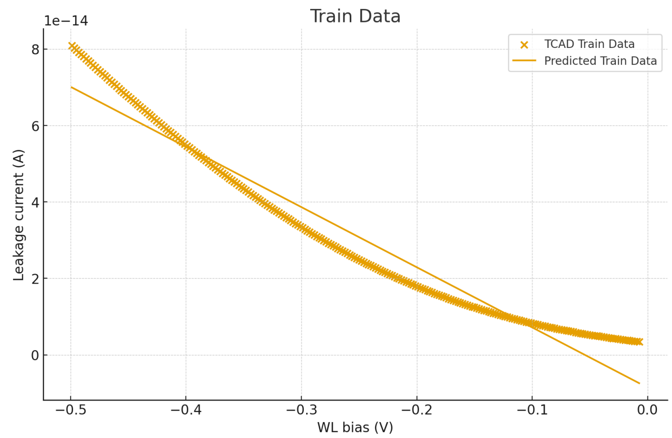

Fig. 2. Leakage current predition model using Linear regression based training data

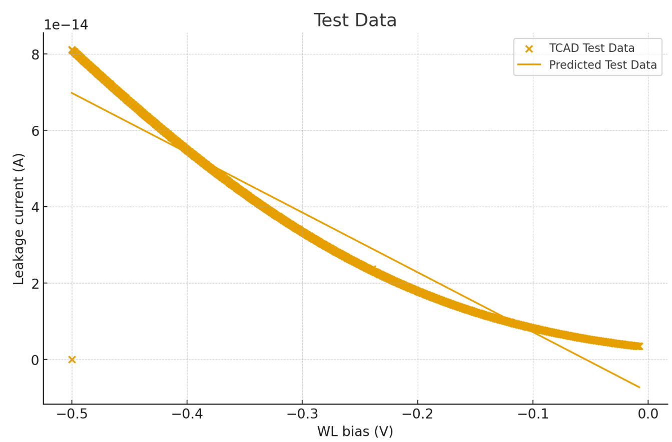

Fig. 3. Leakage current predition model using Linear regression based test data

capture the dominant trend without introducing unnecessary degrees of freedom.

The suitability of the linear regression model over the MLP model can be attributed to the characteristics of the dataset. The MLP model is designed to capture nonlinear relationships among multiple input variables, making it effective for complex, high-dimensional data. However, the dataset used for leakage current prediction consists of two-dimensional data with a single input and a single output. Therefore, the linear regression model is more appropriate than the MLP model for this case.

IV. CONCLUSION

In this study, a machine learning-based prediction model for DRAM leakage current was developed. Three machine learning algorithms were applied for model development, and the results showed that the linear regression model was the most suitable due to the two-dimensional characteristics of the leakage current data. The proposed prediction model offers a advantage in reducing computation time and cost compared to conventional TCAD-based simulations. Furthermore, by minimizing prediction errors to improve accuracy and extending this work to temperature dependent leakage current prediction in future work, this approach is expected to contribute to the development of high-performance DRAM devices.

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