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A Data-Driven ANN-Based Model for FeCAP & FeFET: Orienting to SPICE and Circuit Design

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***Abstract*— Physics-based compact models for emerging non-volatile memories (NVMs) are often limited by the complex interactions of microscopic domains and defects that are difficult to capture analytically, resulting in reduced accuracy and simulation efficiency. To address this challenge, a machine learning (ML)-based approach is proposed using artificial neural networks (ANNs) trained entirely on device measurement data, enabling a direct translation of fabrication characteristics into SPICE-compatible circuit models. The resulting models achieve high accuracy (MSE: 0.724, adjusted R^2: 0.998), significantly outperforming physics-based baselines with an 18× lower MSE for polarization and a two-order-of-magnitude precision improvement in FeFET current simulation, while accurately capturing the wake-up process. Furthermore, the model demonstrates robust out-of-distribution (OOD) extrapolation to unseen ferroelectric thicknesses and a 33.7% improvement in simulation speed. These results validate the ML-based approach as a highly efficient, SPICE-compatible solution for next-generation memory.**

***Index Terms*— Device model, machine learning, emerging devices.**

I. Introduction

Compact models are essential for linking device technology with circuit design, as they balance efficiency, accuracy, and SPICE compatibility [1]. However, developing such models for emerging non-volatile memories remains challenging because the interactions among microscopic domains and defects are difficult to capture analytically [2]. These limitations often reduce modeling accuracy and simulation efficiency [3], [4]. To address this, machine-learning (ML)-based compact-modeling approaches have been explored in recent years [5]–[8]. However, most existing ANN-based compact models still rely on simulation data for training or focus on limited device and operating scenarios [9], [10], which restricts their ability to capture realistic variations in fabricated ferroelectric devices.

To the best of our knowledge, this is the first ANN-based compact-modeling framework for FeCAPs and FeFETs trained directly on measurement data and deployed in SPICE. It captures wake-up behavior, supports adaptation to unseen FE thicknesses, and achieves an adjusted R^2 of 0.998. Compared with Preisach-based models, it reduces polarization MSE by 18×, improves current fitting by two orders of magnitude, and shortens simulation time by 33.7%. With representative data, the same framework can be extended to other ferroelectric materials and device platforms.

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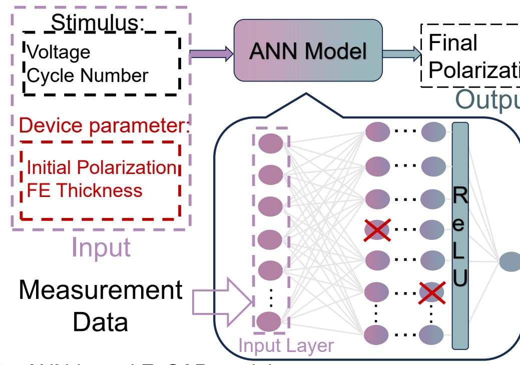

Fig. 1. ANN-based FeCAP model structure.

II. Machine Learning-Based Model Methodology

In this work, we develop a SPICE-compatible (Verilog-A) modeling methodology for a mature fabrication process, and Table I summarizes the inputs and outputs of the FeCAP and FeFET blocks.

TABLE I
I(Input)/O(Output) Specifications for FeCAP and FeFET.

Variable / Feature	Unit / Value
FeCAP Block	
(I) Applied voltage	V
(I) Cycle number	Count
(I) Initial polarization (P_{init})	μC/cm^2
(I) FE thickness (t_{FE})	nm
(O) Final polarization	μC/cm^2
FeFET Block	
(I) Terminal voltages (V_G, V_D, V_S, V_B)	V
(I) Channel dimensions (W/L)	240 nm / 240 nm
(I) Inherited ($N_{\text{cycle}}, P_{\text{init}}, t_{\text{FE}}$)	—
(O) **Drain current** (I_D)	**A**

Fig. 1 illustrates the structure of the proposed model, which can be viewed as a black-box predictor that maps given inputs to outputs. The model inputs are classified into two groups: *electrical stimuli* and *device parameters*. The *electrical stimuli* features include the applied voltage and the cycle number (i.e., the number of write operations accounting for the wake-up effect [11]). The *device parameters* include only those

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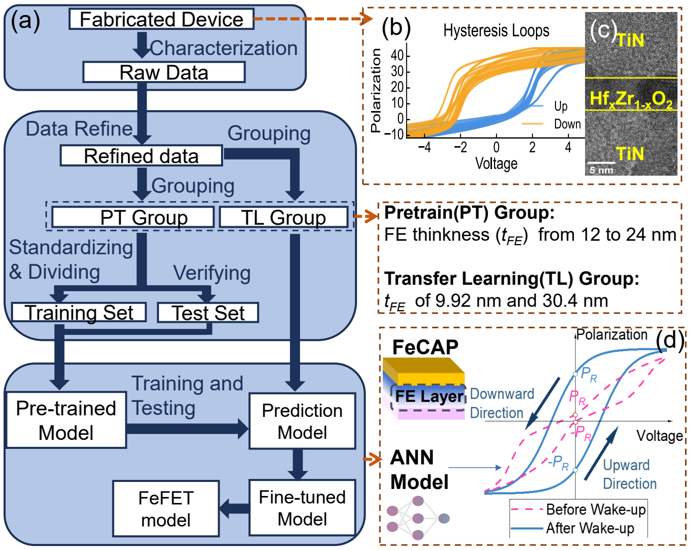

Fig. 2. (a) Flowchart of the ANN-based FeCAP model design. (b) Measured *P–V* hysteresis curve under uniform fabrication conditions. (c) TEM image. (d) Fitting and predicting the *P–V* curves.

bridging fabrication and model design, such as the initial polarization and the ferroelectric layer thickness (t_{FE}). The polarization is defined as the boundary charge Q normalized by the capacitor area A [12], with the initial polarization referring to the predefined state prior to wake-up. To reduce input dimensionality and training effort, some FE-material-related parameters [13], even if important for a physics-based modeling [14], are here excluded and assumed constant in a mature fabrication process. Under this low-dimensional input formulation, a feed-forward ANN is adopted. It is solver-friendly for SPICE deployment. The model predicts the final polarization and is trained directly on measurement data without explicit physical equations. Fig. 2 outlines the three-step development process of the proposed model. Next, we describe this process step by step.

A. Device Fabrication and measurement

The TiN/$Hf_xZr_{1-x}O_2$/TiN FeCAPs (TEM in Fig. 2c) were fabricated per [15] with t_{FE} ranging from 9.92 to 30.4 nm. Under uniform fabrication conditions, a set of experimentally obtained polarization–voltage hysteresis curves is shown in Fig. 2 (b).

B. Data Processing

The first step of data processing is outlier detection, which involves two sub-steps: (1) Initial screening to exclude broken devices, and (2) Magnitude filtering to eliminate extreme points. This step yields a dataset of 124 devices. After processing the data, devices were categorized into two groups based on their FE thickness as shown in Fig. 2: 1) Pre-training (PT) group: devices with $t_{FE} \in [12, 24]$ nm, 2) Transfer Learning (TL) group: devices with t_{FE} of $9.92\,\mathrm{nm}$ and $30.4\,\mathrm{nm}$. This setup evaluates the model on unseen data with t_{FE} outside the training range. A standardization was performed for the PT and TL-group separately to ensure consistency and comparability of the features. Finally, the PT-group was further divided into the ‘training set’ (70%) and the ‘test set’ (30%), with all data from each device assigned exclusively to one set, avoiding bias in the evaluation process. All measurements were conducted at room temperature under fixed electrical test conditions. While fabrication parameters like annealing temperature were excluded due to their negligible contribution to accuracy, the framework is highly scalable and can readily incorporate ambient temperature as an additional input feature in future temperature-dependent studies.

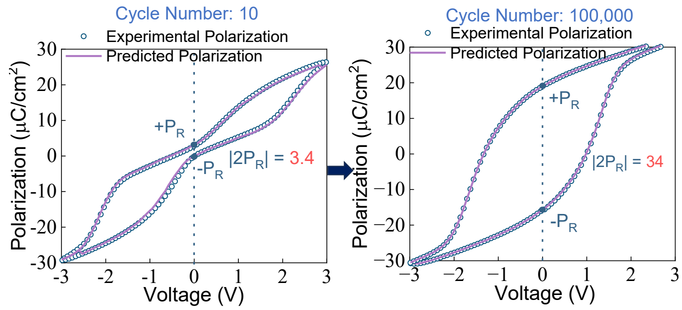

Fig. 3. The results indicate that the remnant polarization ($\boldsymbol{P_R}$) progressively increases with the number of cycles during the wake-up process and the fully woken-up state is defined by saturation of $\boldsymbol{P_R}$.

C. Model Training and Transfer Learning

The neural network (Fig. 1) was optimized via architecture search, resulting in a Multi Layer Perceptron with four hidden layers with 36, 180, 210, and 180 neurons, respectively. Leaky ReLU was adopted as the activation function, and a 5% dropout rate was used to mitigate overfitting. Model accuracy was evaluated using MSE, adjusted R^2, RMSE, and MAE. A data-efficiency analysis further shows that MSE < 1 is achieved with only 31 devices, while the performance starts to saturate at around 62 devices.

The adaptation flow consists of two stages: (1) out-of-distribution (OOD) extrapolation on the TL group without retraining, and (2) fine-tuning for rapid adaptation to new devices. Robustness was evaluated through cross-validation by systematically excluding TL groups. The trained model was then converted to Verilog-A and integrated with a MOSFET model for FeFET simulation. The exported Verilog-A block was numerically verified against the Python model under identical inputs. Although adaptation is required for different fabrication processes, the cost remains low, with fine-tuning taking only $\sim$2 minutes in our setting. The same workflow is applicable to both FeFET and FeRAM.

III. Result and Discussion

In this section, we report the results in three parts: (1) training performance on the PT-group test set, including wake-up fitting; (2) OOD extrapolation and fine-tuning on the TL group; and (3) FeFET simulation using the ANN-based FeCAP model in Verilog-A.

A. Training Results

Fig. 3 presents the P-V curve fitting result for one FeCAP obtained from our trained model, demonstrating the high accuracy of our model. In addition, our model accurately simulates the wake-up process, where the remanent polarization exhibits substantial growth as the number of cycles increases. Predicting the wake-up behavior in physics-based compact models is challenging due to the complex mechanisms [3], [16], [17]. Our ANN-based model successfully simulates this process, since it relies on data analysis rather than physical representation.

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TABLE II

COMPARISON WITH DIFFERENT MODELS. UNITS: MSE IN $(\mu\mathrm{C/cm^2})^2$; RMSE AND MAE IN $\mu\mathrm{C/cm^2}$; ADJ. R^2 IS UNITLESS.

Model	MSE	RMSE	MAE	Adj. R^2
Physical-based Model [16]	12.866	3.856	1.971	—
Random Forest	31.026	5.570	4.094	0.898
SVR	17.110	4.136	2.681	0.944
LASSO	81.024	9.001	6.142	0.814
Our Work	**0.724**	**0.851**	**0.343**	**0.998**

Note: Random Forest, SVR, and LASSO were implemented as baseline models and were trained and evaluated on the same experiment set-up. The source code is publicly available at our repository.

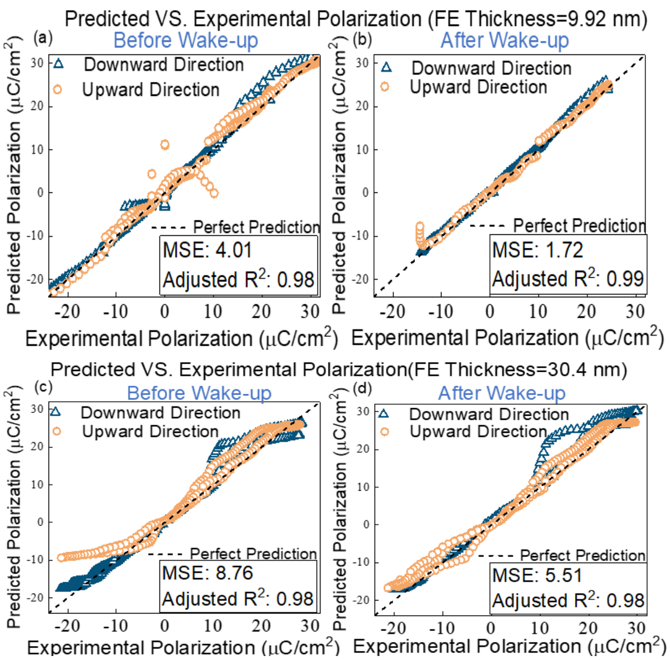


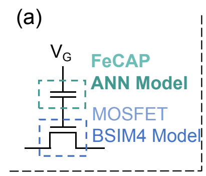
Fig. 4. Comparison of Experimental vs. Predicted Polarization using pre-trained model without further training for untrained FE thicknesses.

We evaluate our model against several classical machine learning baselines, as well as a compact model developed following [16], with results summarized in Table II. The ANN achieves a test MSE of 0.724 and an adjusted R^2 of 0.998, accounting for 99.8% of the polarization variance while accurately capturing the complex P–V relationship. Our model consistently outperforms all other evaluated regression models across all metrics. In particular, the compact model based on [16] yields a significantly higher MSE of 12.866, as reported in Table II. These results demonstrate the superior accuracy of our model in capturing device behavior.

B. OOD Extrapolation and Fine-Tuning Results

In the OOD extrapolation stage, we applied the model to the TL-group without retraining. Fig. 4 compares measured and predicted polarization for t_{FE} of 9.92 and 30.4 nm, with directions indicating initial polarization states. While MSE and adjusted R^2 slightly decrease compared to the PT-group, the prediction error remains superior to the physics-based model ([16]) in Table II. This confirms the model's strong predictive capability for untrained t_{FE}.

The model was fine-tuned using 14-fold cross-validation based on t_{FE} subsets to ensure robustness across data partitions. In each iteration, 13 subsets formed the PT group, while the remaining subset served as the TL group for verification. This iterative process significantly improved performance compared to the results in Fig. 4, achieving a mean MSE of 0.672 and an average adjusted R^2 of 0.995.



	MSE	Wake -up	Speed (ms)
ANN Model	10^{-15}	√	1.5x
Preisach Model	10^{-13}		1.0x

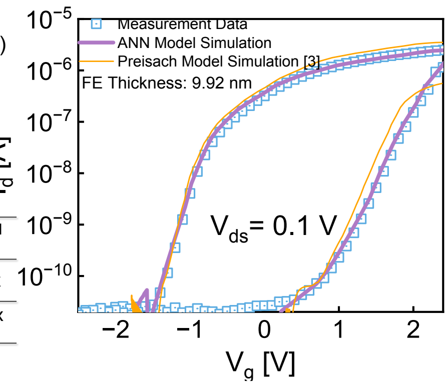


Fig. 5. (a) FeFET structure and modeling; (b) Fitting result of ANN-based model and Preisach model

C. FeFET Modeling and Fitting

The FeCAP model was exported to Verilog-A and combined with a BSIM core to build the FeFET model, as shown in Fig. 5(a). In this implementation, the ANN-based FE block captures the history-dependent ferroelectric response, while BSIM governs channel transport, terminal-voltage dependence, and baseline capacitances. The resulting FeFET cell can be used directly in standard SPICE testbenches. Accordingly, this brief letter focuses on transfer-hysteresis validation through the I_d–V_g characteristics.

The model was fitted to the measurement data of a FeFET with the same FeCAP structure as in [18]. For comparison, we also implemented a Preisach-based Verilog-A compact model and calibrated it using the same data. Fig. 5(b) compares the measured and simulated I_d–V_g characteristics of both models. Our model yields an MSE two orders of magnitude lower than the Preisach model and also captures the wake-up process, although the absolute MSE values are small because of the low drain-current magnitude. Under identical transient testbench settings, the ANN model achieves a 33.7% reduction in the transient CPU time. This speedup mainly comes from avoiding the internal root solving and heavy state-history updates required by the physics-based baseline.

IV. CONCLUSION

This work presents a data-driven, SPICE-compatible model for FeCAPs and FeFETs trained on measurement data. It outperforms physics-based models in both accuracy (MSE 0.724 vs. 12.866) and speed (33.7% faster), captures wake-up behavior, and shows robust OOD extrapolation and rapid fine-tuning adaptability. As a measurement-driven compact model, it trades some physical interpretability for improved fitting accuracy and deployment efficiency, and is therefore intended for the characterized voltage/thickness domain. With representative data, the same workflow can be extended to other FE stacks and memory devices, such as FeRAM, with only data/interface updates. Code availability: The anonymous repository containing the ANN training scripts, baseline implementations, and the Python-to-Verilog-A conversion flow is available at: `https://github.com/wangkayn/FeCAP-ANN-Model`.

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