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Neural Network Assisted Compact Model for Accurate Characterization of Cycle-to-cycle Variations in 2-D *h*-BN based RRAM devices

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Introduction: Resistive random-access memory (RRAM) is one of the most promising candidates for realizing the next generation of non-volatile memories and neuromorphic computing architectures. Although these devices have been extensively researched; accurate modeling of non-ideal effects such as cycle-to-cycle (C2C) variation and resistance drift remain challenging due to the stochastic nature of filament formation and filament evolution [1-3]. In this paper, resistive switching (RS) in 2-dimensional (2D) *hexagonal* Boron Nitride (*h*-BN) is demonstrated, and techniques for modeling C2C variations are presented. Using an autoregressive neural network, a VerilogA model for RRAM is created to accurately reproduce experimentally observed C2C variations. This modeling approach is intended to aid circuit designers in evaluating stochastic phenomenon at the large array level and model emerging devices using advanced materials in their early phase of technology development.

***h*-BN RRAM Fabrication and Characterization:** To fabricate resistive switching (RS) devices, multilayer *h*-BN films were deposited onto electropolished copper foils at 1050° C using CVD (Fig.1-2). The Raman spectrum of the deposited thin film (Fig.3) confirmed the correct *h*-BN structure formation. Ti (5nm)/Au (50nm) metal stack was deposited using UV aligner for both top and bottom electrodes. The synthesized *h*-BN is transferred onto the patterned bottom electrode using PMMA [polymethyl-methacrylate]-based bubbling process [5] before the top metal electrode was deposited. For 20 devices, I-V characteristics cycles were recorded (each for 5 SET/RESET cycles) totaling 253,698 unique I-V datapoints.

Neural Network Assisted RRAM Compact Model: The autoregressive neural network considers starting resistance (R_{START}) and cycle number (N_{CYCLE}) to predict ending resistance (R_{END}) and switching voltage (V_{SWITCH}) for any given cycle. The process of extracting these features and preconditioning the data was automated to enable the proposed method for future applications requiring much larger experimental data sets. 32 hidden units with ReLu activation provide complex non-linear regression. First, inputs are normalized (assigned to a scale of 0-1) and higher order (up to 3rd order) terms are recombined to increase model complexity (Fig.6). The model is trained until validation loss shows no improvement for 10 training iterations (epochs). After a total of 324 training epochs were performed, the model's regression (Fig.7) was graphically inspected and confirmed to have good fit. To reproduce experimental variations, the test data was compared to the model regression and recompiled as cumulative distribution functions (CDF)(Fig.8). Random switching characteristics can likewise be reproduced in an autoregressive-fashion via following steps:

1. R_{START} is randomly sampled from an initial CDF. N_{CYCLE} is 1, indicating first SET.
2. The neural-network (Fig.6) considers N_{CYCLE} and R_{START} to predict V_{SWITCH} and R_{END} (Fig.4).
3. CDF is randomly sampled. The resulting variation is applied to V_{SWITCH} and R_{END}.
4. R_{END} becomes R_{START} for the following cycle. N_{CYCLE} is incremented. Steps 2-4 are repeated for further cycle predictions. Generated sequences are saved as random seeds for VerilogA model.

To demonstrate accurately reproduced C2C variations, 20 sequences are generated and compared to the 20 experimental sequences (Fig.9). When the same data is presented as a distribution (Fig.10) early-cycle forming characteristics are clearly observed in both cases indicating the VerilogA model has accurately reproduced experimentally observed C2C variations. Notably, the model works well for cycles provided in the training set (cycles 1-5 in our case) although further investigation is required to accurately extrapolate beyond training data set.

Conclusion: In this work, we demonstrate RS in 2-D *h*-BN using CVD, PMMA techniques and develop neural network assisted compact model to capture C2C variations for evaluating the effectiveness of emerging RRAM devices utilizing advanced materials. The proposed compact modeling approach is suitable for devices with large sets of experimental data. The methods described and can be extended to other novel devices exhibiting temporal and activity dependent stochastic variations.

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References: [1] S. Yu, X. Guan and H.S.P. Wong, IEDM, 2011 IEEE International (pp. 17-3). [2] N. Raghavan, R. Degraeve, A. Fantini, IEDM, 2013 IEEE International (pp. 21-1). [3] R. Degraeve, A. Fantini, N. Raghavan, Microelectronic Engineering, 147, pp.171-175, 2015. [4] F.M. Puglisi, L. Larcher, C. Pan, IEDM, 2016 IEEE International (pp. 34-8). [5] G. Kim, A.R. Jang, H.Y. Jeong, Nano letters, 13(4), pp.1834-1839, 2013.

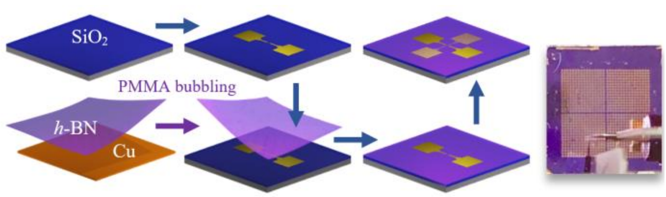


Fig.1: *h*-BN devices fabricated via PMMA bubbling method, the final die includes 1024 devices.

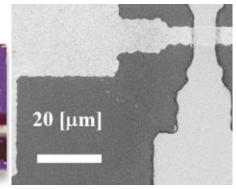


Fig.2: SEM of device region, apx. 100[μm^2].

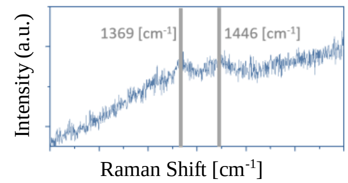


Fig.3: Raman shift at 1369.7 cm^{-1}, the *h*-BN E_{2g} phonon frequency

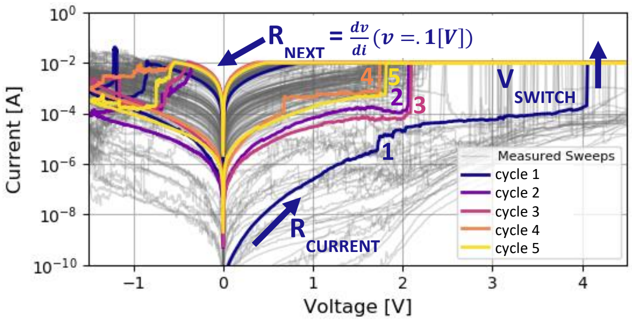


Fig.4: DC sweeps demonstrate significant C2C variation. Sweeps for a single device are colored. All DC sweeps are shown in gray. Automatically extracted features are labeled.

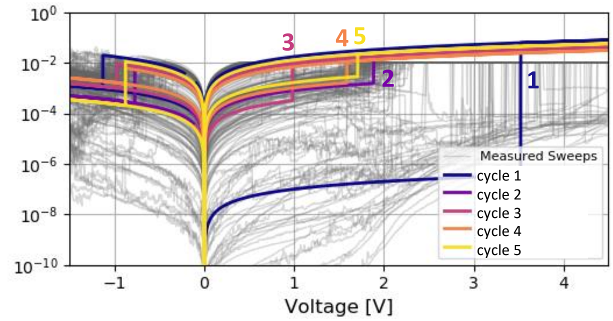


Fig.5: DC sweeps simulated in Cadence using developed VerilogA model capture C2C variations consistent with test measurements.

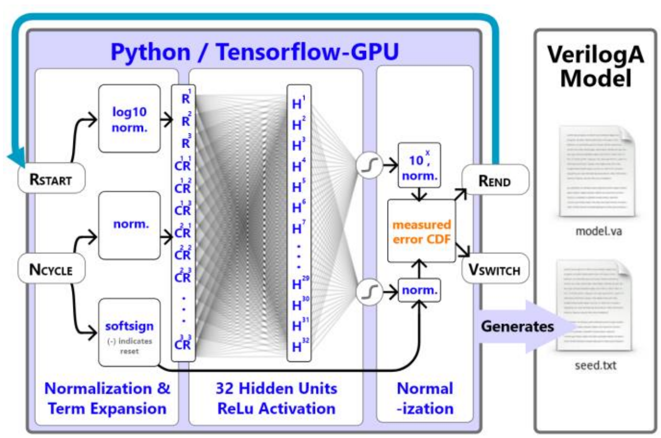
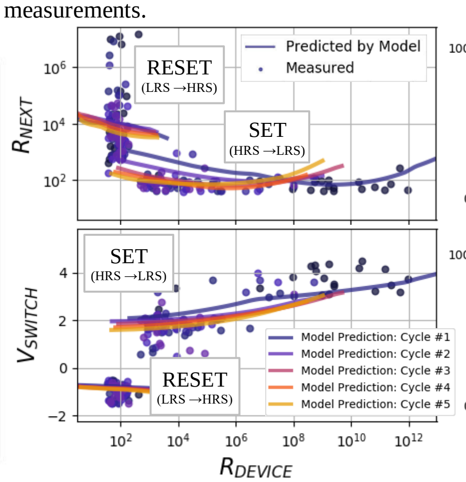


Fig.6: Representation of the autoregressive neural network model which considers R_{START} and cycle number (N_{CYCLE}) to predict ending resistance (R_{END}) and switching voltage (V_{SWITCH}). Generated sequences are exported as VerilogA model seeds.



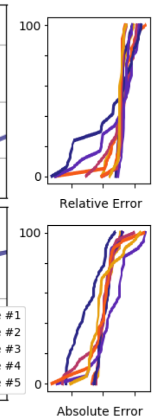


Fig.7 All measured data is compared to the regression learned by the neural network. Measured data demonstrates significant deviation from the model which are captured by error CDFs.

Fig.8: CDFs demonstrate error is cycle-dependent and non-gaussian

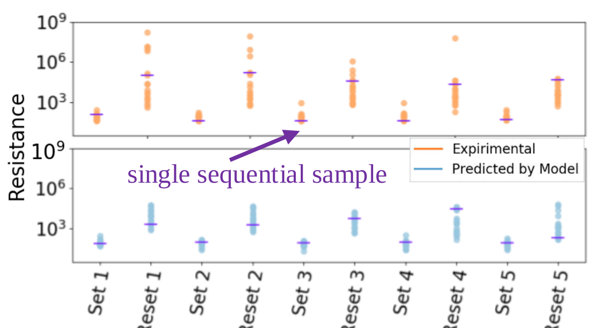


Fig. 9: Top: cycle-to-cycle variations demonstrated sequentially for all 20 measured devices and 20 simulated devices. A single sequential sample is highlighted.

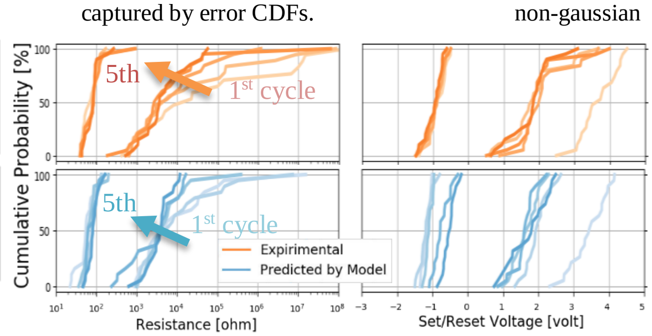


Fig. 10: Cumulative distribution for the sequence shown in Fig.9; distribution of resistance states and switching voltage confirm model reproduces C2C variations consistent with physical devices.