Multiscale modeling and simulation of resistive switching memory (RRAM) for reliability and neuromorphic applications

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In the era of artificial intelligence (AI), efficient storage and processing of huge amounts of data play a crucial role to fuel the impressive transformation of today's society. To this goal, novel paradigms aiming at removing the latency and energy barriers affecting conventional computers, e.g., by taking inspiration from human brain such as neuromorphic computing, and novel non-volatile memory concepts have been extensively explored. In this scenario, the resistive-switching memory (RRAM) has attracted great interest thanks to its simple metal-insulator-metal structure, CMOS compatibility, low-power operation, and multilevel resistance, rapidly becoming an excellent candidate for implementing neuromorphic computing in hardware [1-2].

However, RRAM technology suffers from reliability issues including device-to-device variability, linearity, retention, and cycling endurance which, despite the strong efforts made in the recent years, have not been solved yet. The solution of these non-idealities necessarily requires a deep insight of the physical mechanisms governing RRAM operations, which makes the multiscale modeling platforms linking device performance and reliability to material microscopic properties fundamental tools to accelerate RRAM technology development [3-4].

In this paper, we first review the physical mechanisms and operation of RRAM devices. Secondly, RRAM reliability will be addressed exploiting simulation results achieved by Ginestra™ multiscale material-to-device simulation platform (**Fig. 1**) [5]. Ultimately, we will discuss the RRAM operation as a synaptic weight in a neural network (**Fig. 2**), highlighting the advantages and drawbacks of this memory device depending on the neuromorphic application.

References

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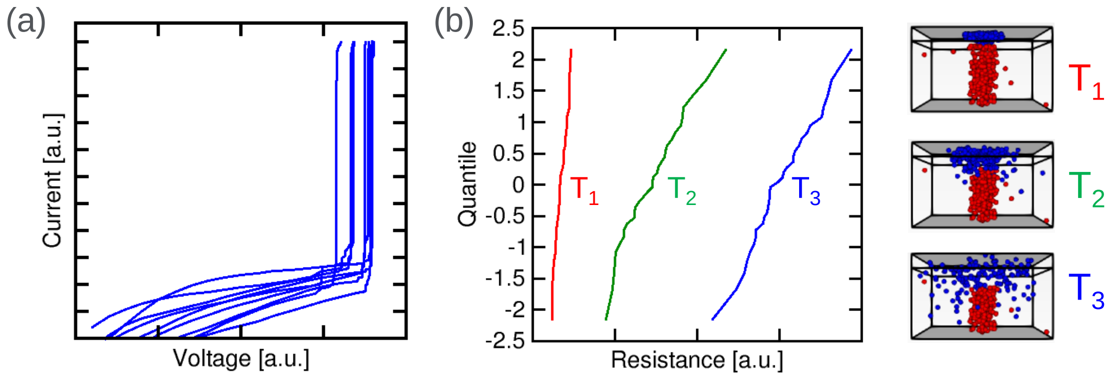

Fig. 1 (a) Calculated forming I-V characteristics affected by device-to-device variability. (b) Calculated LRS retention distributions exhibiting a shift at higher resistance for increasing temperature (T_1<T_2<T_3) due to the T-accelerated gap opening caused by recombination of oxygen ions (blue spheres) with the oxygen vacancies (red spheres) of the conductive filament.

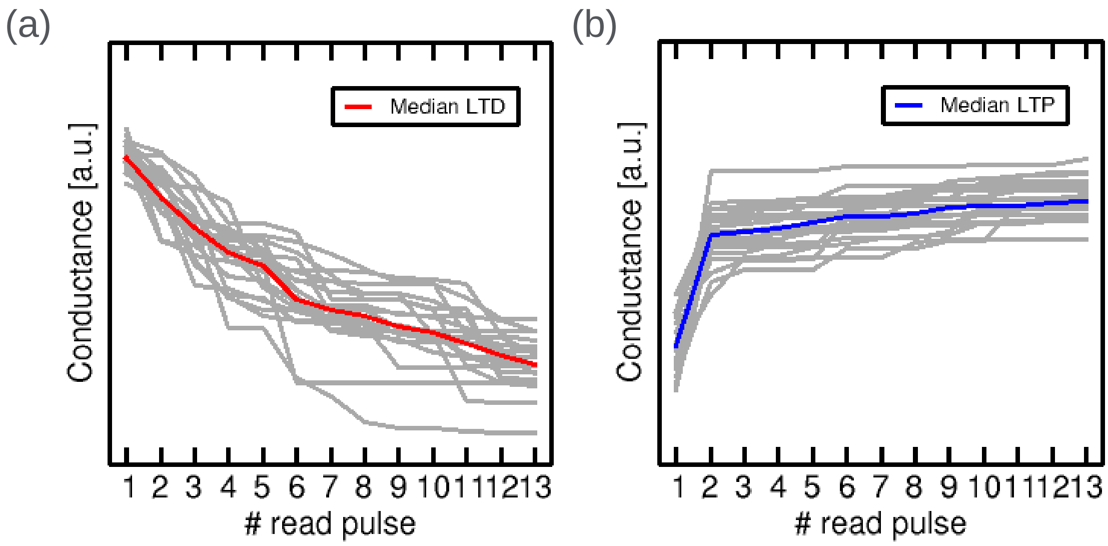

Fig. 2 (a) Calculated long-term depression (LTD) for 20 RRAM-based synaptic weights by application of a pulse train with increasing voltage amplitude (in absolute value) evidencing typical gradual conductance decrease. (b) Calculated long-term potentiation (LTP) for 20 RRAM-based synaptic weights by application of a pulse train with increasing voltage amplitude evidencing typical abrupt conductance increase.