Ph.D. in Information Technology
Thesis Defenses

July 23rd, 2024
at 9:00 a.m.
Room Bio1

Lorenzo CATTANEO – XXXVI Cycle

DESIGN AND EVALUATION OF MEMRISTOR-MEMORY-BASED STRONG AND WEAK PHYSICAL UNCLONABLE FUNCTIONS

Supervisor: Prof. Daniele Ielmini

Abstract:

In recent decades, the microelectronics industry has witnessed exponential growth in performance and computing capabilities, driven by the relentless scaling of electronic components, resulting in an increasing number of transistors on integrated circuits (IC). However, this scaling trajectory is reaching its limits due to structural and physical constraints, such as the heat wall and the consequent ceiling imposed on clock frequency. Additionally, conventional computing systems based on the von Neumann architecture face inherent challenges stemming from the separation of processing and memory units, leading to significant performance disparities known as the memory wall. This architectural setup proves inefficient, particularly in applications requiring extensive data processing, such as machine learning, due to the sluggish data transfer rates between the CPU and memory. To address these constraints, especially in the era of the Internet of Things (IoT) and Big Data, interest has surged in alternative computing paradigms like in-memory computing (IMC), neuromorphic computing, and stochastic computing. In this context, emerging memory technologies, notably memristors such as resistive switching random access memory (RRAM), phase change memory (PCM), ferroelectric memory (FeRAM), and spin-transfer torque magnetic memory (STT-MRAM), are being explored for their non-volatility, scalability, low power consumption, and fast operation, as well as their compatibility with the complementary metal oxide semiconductor (CMOS) process. However, leveraging these devices in practical applications requires addressing the challenges associated with their stochastic nature. On the other hand, it is precisely the inherent stochasticity of these devices that becomes a strong point in favor of their use in security-related applications.

This doctoral thesis aims to explore the development of Physical Unclonable Functions (PUFs) based on emerging non-volatile memory (NVM) technologies. In the realm of hardware security, PUFs can provide a unique physical fingerprint to devices in the Internet of Things (IoT), which is a valuable means of enhancing security through the generation of unique and volatile cryptographic keys with no need to store them in non-volatile memory. By capitalizing on the inherent stochastic characteristics of emerging NVM devices, this research work seeks to develop PUFs that offer enhanced security features while addressing the limitations associated with their use in practical applications and proposing solutions to mitigate them.

Through a comprehensive analysis, extensive physics-based simulations, and experimental validations, the dissertation contributes to advancing the understanding and utilization of emerging NVM technologies for secure hardware authentication and cryptographic applications.

Alessandro MILOZZI – XXXVI Cycle

EMERGING MEMORY DEVICES & SYSTEMS FOR BIOLOGICALLY PLAUSIBLE NEUROMORPHIC COMPUTING

Supervisor: Prof. Daniele Ielmini

Abstract:

Nowadays, the volume of data produced in our society is exponentially surging, as is its variety and complexity. Automotive, smart cities, and Industry 4.0 are just a few examples of trends that are accelerating the demand for increased computational and storage capacities. Having surpassed its "second winter", Artificial Intelligence (AI) today offers a tool to address these new challenges. However, in its practical implementations, AI tends to overload computing infrastructures and systems, leading to an even more dramatic increase in computational demand. The underlying issue is rooted in the architecture of modern computers, proposed in 1945 by Von Neumann. The Von Neumann architecture, which separates the computing unit from the memory, has allowed us to build flexible, general-purpose machines over the past 70 years. However, this architecture is now showing significant inefficiencies primarily due to the need to move data between the two units. This problem is exacerbated by an asymmetry in the rate of technological improvement between memory units and processing units and by approaching the physical limit for scaling CMOS technology. In this context, Neuromorphic Computing emerges: started from the seminal work of Carver Mead in the late ’80s, this new paradigm draws inspiration from biological neural structures to emulate the functioning and efficiency of the brain at the hardware level. In the brain, there is no separation between computing and memory: the two fundamental units, neurons and synapses, work in synergy, and the concepts of memory and computing merge. Beyond a shift towards in-memory computing, biological networks are characterized by their plasticity, or the ability to continuously adapt to stimuli. It is neuronal plasticity that is responsible for our ability to remember, learn, and adapt through a myriad of complex plasticity mechanisms that together result in energy efficiency and computational capabilities that are unimaginable in their artificial counterparts today. However, new paradigms usually require new technologies, and this is where resistive switching devices come into play. These emerging memory devices are not only viable for supporting future technological scaling but potentially can implement mechanisms that emulate the plasticity of the human brain. Expanding and investigating this set of plasticity and learning mechanisms is the open challenge of neuromorphic computing, leading to scalable, efficient, and biologically plausible systems.
This doctoral thesis focuses on expanding the plasticity mechanisms achievable through the dynamic properties of memristive devices and their use in biologically plausible neuromorphic

systems, where this latter component is crucial for bridging the gap between models of computational neuroscience and hardware for AI. The approach of this work is based on moving computation inside the device by exploring its intrinsic dynamics resulting from its physical properties. A framework is presented that defines the boundary between static and dynamic memory in neuromorphic systems and how this impacts the emulation of biological mechanisms. This maps onto three structural areas of the work, analogous to properties present in biological neural networks: external factors that modify plasticity, internal dynamic factors that act on plasticity, and stochasticity.

PhD Committee

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