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Memristor-A Promising Candidate for Neural Circuits in Neuromorphic Computing Systems

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***Abstract*—**The advancements in the field of Artificial Intelligence (AI) and technology has led to an evolution of an intelligent era. Neural networks, having the computational power and learning ability similar to the brain is one of the key AI technologies. Neuromorphic computing system (NCS) consists of the synaptic device, neuronal circuit, and neuromorphic architecture. Memristor are a promising candidate for neuromorphic computing systems, but when it comes to neuromorphic computing, the conductance behavior of the synaptic memristor or neuronal memristor needs to be studied thoroughly in order to fathom the neuroscience or computer science. Furthermore, there is a need of more simulation work for utilizing the existing device properties and providing guidance to the development of future devices for different performance requirements. Hence, development of NCS needs more simulation work to make use of existing device properties. This work aims to provide an insight to build neuronal circuits using memristors to achieve a Memristor based NCS. Here we throw a light on the research conducted in the field of memristors for building analog and digital circuits in order to motivate the research in the field of NCS by building memristor based neural circuits for advanced AI applications. This literature is a step in the direction where we describe the various Key findings about memristors and its analog and digital circuits implemented over the years which can be further utilized in implementing the neuronal circuits in the NCS. This work aims to help the electronic circuit designers to understand how the research progressed in memristors and how these findings can be used in implementing the neuronal circuits meant for the recent progress in the NCS.

***Keywords*—**Analog circuits, digital circuits, memristors, neuromorphic computing systems.

I. Introduction

HUMAN society is transforming from the information era to the intelligence era. Various intelligent applications are affecting all aspects of human life including business, education, medical care, security, and other walks of life. This rapid development is due to internet, mobile internet, and internet of things. The emerging technologies such as big data, cloud computing, machine learning, data mining, deep learning, and artificial intelligence (AI) are flourishing and thriving due to massive data and high performance computing hardware.

One of the key artificial intelligence technologies today is neural networks having the computational power and learning ability similar to the brain. Many of our daily operations and services use neural networks such as smartphone voice control, shopping recommendation, voice recognition, face recognition, etc. Recent AI technologies are based on neural networks, for instance, Google's AlphaGo, DeepMind's differentiable neural machine, DeepStack for no-limit poker play, and Stanford's skin cancer classification.

Neural networks find applications in the area of autonomous driving, smart grids, etc but implementation of neural networks has drawbacks due to the energy, area, and time consumption. This is because the real world applications incorporate the learning systems and network models based on neural networks which command a large data/ computation volume for both the training and inference processes. CMOS von Neumann computing systems based neural networks suffers from the bottleneck of restricted bus bandwidth and memory wall that results due to the CMOS downscaling. Large-scale neural networks based applications are energy/ area hungry. Hence neuromorphic computing systems come to rescue the efficient implementation of neural networks [27].

The term 'neuromorphic' was coined by Carver Mead around 1990. He defined neuromorphic systems as artificial systems that share organization principles with biological nervous system. So what are those organization principles? A brain is differently organized than a computer and science is still a long way from understanding how the whole thing works. A computer is easy to understand by comparison. Features (or organization principles) that clearly distinguish a brain from a computer are massive parallelism, distributed storage, asynchronous processing, self-organization.

Neuromorphic circuits try to incorporate those principles. Whereas a computer by contrast is a synchronous serial machine, with centralized storage and it is programmed.

Research in neuromorphic VLSI can lead to computing machines that are fundamentally differently organized than digital computers. Devising a machine with human like intelligence has been the driving force since ages. This can be achieved by more closely copying the biological process. Although computers are general machines that can simulate any other digital machine and arbitrarily approximate analog processes, neuromorphic machines can outrank them in terms of speed, energy efficacy, and size.

Neuromorphic computing system comprises of the synaptic device, neuronal circuit, and neuromorphic architecture similar to the human brain. Memristor crossbars are promising candidate for neuromorphic computing. As argued by Zhang, when it comes to neuromorphic computing, the behavior of the neuronal memristors needs to be studied thoroughly in order to fathom the neuroscience. Also, more simulation work is needed to use the existing device properties in order to provide guidance to the development of future devices for different

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performance requirements.

This literature is a step in this direction where we describe the various key findings about memristors and its analog and digital circuits implemented over the years which can be further utilized in implementing the neuronal circuits in the NCS. This paper aims to provide help to electronic circuit designers to understand how the research progressed in memristors and how these findings can be used to implement the neuronal circuits meant for the recent progress in the Neuromorphic computing systems. Describe the work in all the other sections.

II. Neuromorphic Computing Systems

Neuromorphic computing is an inter-disciplinary area aiming to emulate the computational principles of biological neural systems and to utilize such principles to solve complex and computationally intensive problems. The discipline originated with the goal of constructing silicon models of Biological neurons and synapses, based on the observation that the basic Physics governing the flow of current across a semiconductor junction and Biological "junction" in an ion channel were the same [25]. Neuromorphic computing systems have been proposed for efficient implementation of neural networks. NCS consists of the synaptic device, neuronal circuit, and neuromorphic architecture**.** However, the CMOS von Neumann computing systems based hardware implementation of neural networks suffers from the bottleneck resulting due to the CMOS downscaling namely, the bus bandwidth and the memory wall [27]. Hence, applications based on large-scale neural networks are energy/area hungry.

Neuromorphic computing systems can be used for the implementation of artificial neural networks and spiking neural networks.

One such system (NCS) proposed is memristor crossbars based neuromorphic computing. With memristor as the synaptic device and crossbar as parallel architecture, memristor crossbars were proposed as a promising candidate for neuromorphic computing [27].

A. Neuromorphic Engineering

Neuromorphic Engineering is a concept developed by Carver Mead in late 1980s. It describes a group of customized electronic circuits that either mimics organic behavior or is inspired from biological architectures. To understand neuromorphic engineering an understanding of the characteristics of neuromorphic circuit elements is necessary.

Neuromorphic circuits are inspired by the organizing principles of biological neural circuits. Their computational primitives are based on physics of semiconductor devices [24]. Neuromorphic systems architectures often rely on collective computation in parallel networks. Adaptation, learning and memory are implemented locally within the individual computational elements. Transistors are often operated in weak inversion (below threshold), where they exhibit exponential I-V characteristics and low currents. These properties lead to the feasibility of high-density, low-power implementations of functions that are computationally intensive in other paradigms.

Application domains of neuromorphic circuits include silicon retinas and cochleas for machine vision and audition, real-time emulations of networks of biological neurons, and the development of autonomous robotic systems.

B. Neuromorphic Electronic Circuits

Neuromorphic electronic circuits are inspired by the nervous system that either help verifying neuro-physiological models, or that are useful components in artificial perception/action systems. Research also aims at using them in implants. These circuits are computational devices and intelligent sensors that are differently organized than digital processors wherein storage and processing capacity is distributed. They are asynchronous and use no clock signal and are often purely analog and operate time continuous. They are adaptive or can even learn on a basic level instead of being programmed. A VLSI designer must be able to exploit mechanisms employed by the nervous system for compact energy efficient analog integrated circuits.

III. Memristors in Neuromorphic Computing Systems

A. Memristor in Neuromorphic Engineering

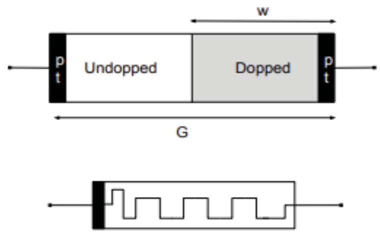

Fig. 1 Generic Memristor structure and its symbol

Fig. 1 illustrates the general structure of memristive devices. Doped and undoped regions form the two regions of memristors in series. Ideally, the resistance difference between doped and undoped region is very high. The overall device resistance is a function of doping ratio(w/G), where w the length of the doped region, and G is the thickness of the memristor. The size of these regions can be changed depending on amount and direction of the charge that flow through the device. For instance in a voltage-controlled, by applying a positive voltage increases the thickness of doped region increases until w = 1, and the resistance will be very low or device is in ON state [26]. Ideally, memristors can be programmed to represent analog memory or various intermediate resistance states between high resistance states and low resistance states. Memristors are promising candidates for implementing the synaptic connection between pre-synaptic and the post-synaptic neurons due to their programmable resistive states. There has been significant activity dedicated to developing memristive-based neuromorphic systems [27].

B. Memristor Based Neuromorphic Chip Design

Designing memristor based Neuromorphic chip has been a research interest since 2008. Memristor crossbars can store the synaptic information. Since, RRAM structure is the mainstream of fabricated memristor, memristor based neuromorphic circuit should be very compatible with crossbar architecture. The first Neuromorphic chip Mazer was an nMOS integrated circuit designed in 1977. The whole algorithm was implemented on a hardware level. Mazer was a highly customized computing architecture. In subsequent years, focused on realizing biological organs on Neuromorphic engineering

IV. Memristors Models: Neural Circuits

A. History and Mystery of Memristor:

Memristor was introduced in 1971 [1], the first experimental prototypes were only recently demonstrated by HP Labs [2]. Hypothesized in 1971 by Leon Chua memristor became a new candidate in the group of basic circuit components. In 1971 Leon Chua, presented a seminal paper titled `Memristor - The Missing Circuit Element' in which he proposed a new two-terminal circuit element-called the Memristor characterized by a relationship between the charge and flux linkage [1]. He introduced it as the fourth basic circuit element (the other three being R, L and C).

Although the notion of a memristor was widely accepted, it did not become a hot research topic immediately. Physical Memristor became a reality later in 2008 when Strukov et. al. reported an actual working prototype in `The Missing Memristor Found' where they showed, that Memristance arises naturally in nanoscale systems in which solid-state electronic and ionic transport were coupled under an external bias voltage [2].

These results served as the foundation for understanding a wide range of hysteresis exhibiting current-voltage behavior observed in many nanoscale electronic devices.

B. Memristor Modeling and Implementation of Digital and Analog Circuits

During 1971 to 2008, scholars discussed circuit topologies that behave to the definition of Memristor. The use of diodes and other nonlinear circuit components mostly showed a nonlinear relationship between flux and charge. Hence, the first implementation of Memristor was to build circuits with complex dynamics, later came to be known as chaotic circuits [3].

Memristor became a popular topic of research after 2008, as it was now available for research purpose. After the physical Memristor was made realizable in 2008, a significant quantum of research work in this field was carried out including the Memristor modeling and implementation of digital and analog circuits thereby reducing the complexity of the circuits. This was possible because the Memristor was supposed to have a striking feature of memory as it was capable of remembering the amount of current passed through it.

Various Memristor models were also put forward to enable researchers to design simple and efficient circuits [3]-[9].

In 2010, Mahvash and Parker presented a SPICE model for the Memristor which was fabricated at HP Labs in 2008 and validated it by simulating simple circuits [13]. The proposed model opened avenues to design and simulate Memristor circuits using SPICE. In the same year, Rak and Cserey came out with a new simulation program with integrated circuit emphasis macromodel of the physically implemented Memristor [10]. It proved to be a powerful tool for engineers to design and experiment new circuits with Memristors. In 2013, Biolek et. al. presented mechanisms for reliable SPICE simulations of Memristors, Memcapacitors and Meminductors wherein they proposed a collection of models of different memory circuit elements and provided a methodology for their accurate and reliable modelling in SPICE [21]. To aid the aspiring researchers in this field, the authors were generous enough to provide netlists for these models in various popular SPICE versions (PSpice, LTspice, HSpice).

While Memristor models were being developed as soon as its physical implementation came into existence, another dimension of research progressed to practically implement the Memristor in analog and digital domains using existing ICs. [15], [16]

The first approach in this direction was in 2010 when Pershin and Ventra presented a practical approach to obtain programmable analog circuits with Memristors [14]. The approach was to apply low voltages to Memristors during their actual operation as analog circuit elements and significantly higher programming voltages to set/alter the Memristor's states. They demonstrated that the state of Memristors did not change during analog mode of operation provided all the signal levels were kept much lower than the programming voltage levels. A year later, in 2011 Shin, Kim & Kang presented various Memristor applications for programmable analog ICs [11]. A fine-resolution programmable resistance was achieved by varying the amount of flux across Memristors. Resistance programming was achieved by controlling the input pulse width and its frequency. A Memristor was subsequently designed for a pulse-programmable mid-band differential gain amplifier with high resolution [12].

A research contribution demonstrating the Memristor characteristics and memristance variation with frequency was presented by Lee & Nickel in 2012, wherein they presented the idea of Memristor resistance modulation for analog applications [17]. It was shown that the linear resistance can be randomly programmed with accuracy and reproducibility. Analog circuits of tunable memristive low-pass and high-pass filters demonstrated frequency tuning by resistance modulation [18]-[21].

As the research progressed on memristor to implement analog filters, their application in the field of biomedical signal acquisition and conditioning came into existence. A major step in this direction was in 2014 when Yener et. al. presented analytical and dynamical models for a Memristor-based high-pass filter and amplifier [23]. In the same year, the same authors also presented their work on frequency and time domain characteristics of a Memristor-based continuous-time low-pass and high-pass filters [22].

More recently, Yener et. al. put forward an ultra-low-voltage ultra-low-power Memristor-based band-pass filter and its application to EEG signal acquisition [27]. Several analog applications of Memristor, its SPICE macro-models and `Memristor Emulators' with Memristor-like behavior were presented. This paper was an extended version of the study where the design of an ultra-low-voltage, ultra-low-power DTMOS-based (emulated) Memristor was presented especially for the Memristor based low frequency biomedical and chaotic applications, which was then used in a second-order Sallen-Key band-pass filter for EEG data processing.

V.Prospects and Conclusion

Digital processors are becoming cheap and powerful nowadays. The processing power of today's processors is way ahead of our daily needs. However, when it comes to scientific research, power consumption of digital processors becomes expensive. Researchers have tried to build Neuromorphic architecture using commercial processors. Emergence of Memristor evokes a new generation of NCS. Memristor based analog and digital applications based circuit models have been reviewed in this article. The future and scope of memristor based NCS is also discussed. Owing to the large density and small power consumption, Memristors are suitable for Neuromorphic computing. Memristors are mainly used as synapse currently. While there is an immense scope of using memristors in neuronal circuits due to their chaotic behavior. On the heels of the rapid development of AI technology, neuromorphic computing using the memristor is to morph into a practical and powerful platform for future AI applications. Progress on memristor based neuromorphic computing systems and efficient implementation of neural networks, challenges remain. If Memristor can be realized in silicon integrated circuits, not only does digital computer saves power for booting but it can lead to distributed processing systems. Researchers have mimicked using sophisticated circuitry. The combination of these two findings will impel the building of powerful Neuromorphic architecture.

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