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Implementation of the Revised Pavlov's Associative Learning Circuit to Avoid Parasitic Training Effects

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To enable organisms to learn behaviors from past experiences, biological systems rely on associative learning, a fundamental mechanism that forms connections between simultaneous events. Developing an electrical counterpart to model this associative learning phenomenon could be highly beneficial for edge AI applications. This study focuses on Pavlovian learning, an associative process in dogs where the sound of a bell becomes linked to food, leading to drooling as a response based on memory. Existing circuit models that attempt to replicate this phenomenon face limitations, especially in distinguishing between different stimuli types and often exhibiting a false learning effect without genuine learning. Consequently, these circuits only demonstrate associative learning under specific signal sequences, failing to do so with other configurations. To address this, we propose a novel circuit architecture using non-volatile memory components, designed to overcome sequencing limitations and enable true associative learning regardless of stimulus order. Simulation results obtained through PSPICE using 0.18 µm CMOS technology validate the functionality of the proposed circuits.

Keywords: Associative learning; ANN; CNN; Memristor; Pavlov's Dog

1 Introduction

The growing interest in brain-inspired computing has driven significant advancements in neuromorphic engineering, a field focused on replicating the neural processes of biological systems using specialized hardware. C. Mead's foundational work on neuromorphic electronic systems introduced analog circuits to emulate neural functions, establishing a basis for brain-inspired hardware design[1]. Building on this, Kandel et al. expanded the understanding of neural mechanisms such as synaptic plasticity and learning, which are critical for modelling memory and adaptive behaviour in artificial systems[2].

Research in neuromorphic systems has extensively explored materials and devices that support synaptic functions. Kuzum, Yu, and Wong reviewed materials and applications in synaptic electronics, underscoring the potential of devices like memristors for emulating plasticity in artificial systems[3]. Eryilmaz *et al.*, demonstrated brain-like associative learning using a nanoscale phase-change device array, showcasing its effectiveness for memory-intensive tasks[4]. Moon *et al.*, presented an analog resistive-switching device capable of hardware-based associative memory functions, highlighting the potential of non-volatile devices in neuromorphic applications[5]. Liu, Zeng & Wen developed a memristive neural network capable of simulating Pavlovian associative memory, further advancing memristor use in artificial memory systems[6]. Hu et al. expanded memristor applications by modelling affective responses in associative memory networks, thereby enhancing neuromorphic computing's scope for more complex, human-like processing[7].

In addition to device-oriented studies, researchers have developed various neural network models and architectures to support associative memory. Yang et al. proposed a memristive Hopfield neural network for associative memory applications, demonstrating high-density, low-power capabilities[8]. The work of Good fellow, Bengio & Courville on deep learning has significantly influenced the development of neural network architectures capable of complex learning, bridging traditional AI and neuromorphic computing[9]. LeCun, Bengio & Hinton contributed key insights into deep learning models, with convolutional networks becoming fundamental for image, speech, and time series processing[10,11]. Graves *et al.*, further advanced the field with their work on recurrent neural networks (RNNs), which proved effective in speech recognition and emphasized the importance of sequence processing in neuromorphic designs[12].

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Memristor-based neural networks continue to evolve in terms of adaptability and functionality. Lv *et al.*, developed a neural network circuit capable of associative learning and forgetting processes using memristor devices, simulating adaptive memory characteristics similar to those in biological systems[13]. An *et al.*, discussed the opportunities and challenges in scaling nanoscale 3D neuromorphic computing systems, focusing on hardware architectures that support dense neural integration[14].

The evolution of neuromorphic memory technologies has been accelerated by advances in materials and device architectures. Wong et al. explored metal-oxide resistive RAM (RRAM) and highlighted its potential as a non-volatile, scalable memory for neuromorphic applications[15]. Pershin & Ventra experimentally demonstrated associative memory in memristive neural networks, showing that memristors can replicate synaptic behaviour seen in biological systems[16]. Building on this, Kuzum et al. proposed energy-efficient programming techniques for nano-electronic synaptic devices, aiming at large-scale implementation of associative and sequence learning models[17].Zhou et al.,[18] showed the viability of memristors in biomimetic circuits by proposing a neuromorphic circuit that illustrates the learning as well as forgetting cycles of human emotions under various musical conditions. According to Wang *et al.*, an emotion circuit that has different effects on memory time interval for positive as well as negative emotion functions may more closely resemble human emotional behaviors[19]. Dou et al., presented a neuromorphic circuit for automated learning that depends on operant-conditioning and has memory and the period of time that passes between the two rewards is ingrained in memory. With these features, the circuit can adjust to complicated situations[20]. Again, Wang *et al.*, used a memristor to propose a dual-mode Pavlov circuit to achieve the learning as well as forgetting function that involves visual and auditory associative memory[21].

Pavlov's foundational research on conditioned reflexes illustrated associative learning through stimulus-response conditioning, which has provided a basis for subsequent work in associative memory modelling[22]. Ziegler and colleagues further developed these concepts by creating an electronic version of Pavlov's conditioning, where memristors were used to simulate associative learning, validating the feasibility of hardware-based learning systems[23].

This paper builds upon these foundational studies by proposing a novel circuit design capable of replicating associative learning. Addressing the limitations of existing models in differentiating stimulus sequences and accurately mimicking synaptic plasticity, this work aims to advance neuromorphic computing for applications in AI and machine learning.

In Section 1, we introduce the associative learning phenomenon described by Pavlov, including a classical conditioning circuit designed to model Pavlovian learning. Section 2 details the memristor model used to validate the circuit designs in this study. Section 3 presents the proposed mixed-signal design, which overcomes the limitations of the existing circuit. Section 4 discusses simulation results, illustrating both the limitations of the traditional circuit and the functionality of the proposed circuit. Finally, concluding remarks are provided in Section 5.

2 Associative learning behavior exhibited in the Pavlov's experiment

In associative learning, a dog naturally drools in response to food due to an unconditioned reflex. Before training, if only the bell rings without food, there is no drooling, as no association exists. During training, the sound of the bell is repeatedly paired with the presence of food. Over time, the dog learns to associate the bell (a neutral stimulus) with food (an unconditioned stimulus). After training, the dog begins to drool at the sound of the bell alone, even if no food is present. This conditioned response demonstrates associative learning, where the bell has become a trigger for drooling based on memory. This is shown in the upper part of the Fig. 1.

The lower part of the figure illustrates "parasitic effects" in classical circuit models that attempt to replicate this learning behaviour. In these models, unintended or incorrect responses can occur due to prolonged or incorrectly sequenced signals. For example, if the bell rings for an extended period without food, the circuit may still trigger drooling, a false learning effect. Similarly, if food is presented alone for too long, the circuit may incorrectly associate it with drooling. These parasitic effects given in the lower part of the Fig. 1 highlight the limitations of traditional circuits in accurately replicating true associative learning, as they may produce false responses outside the intended stimulus pairings.

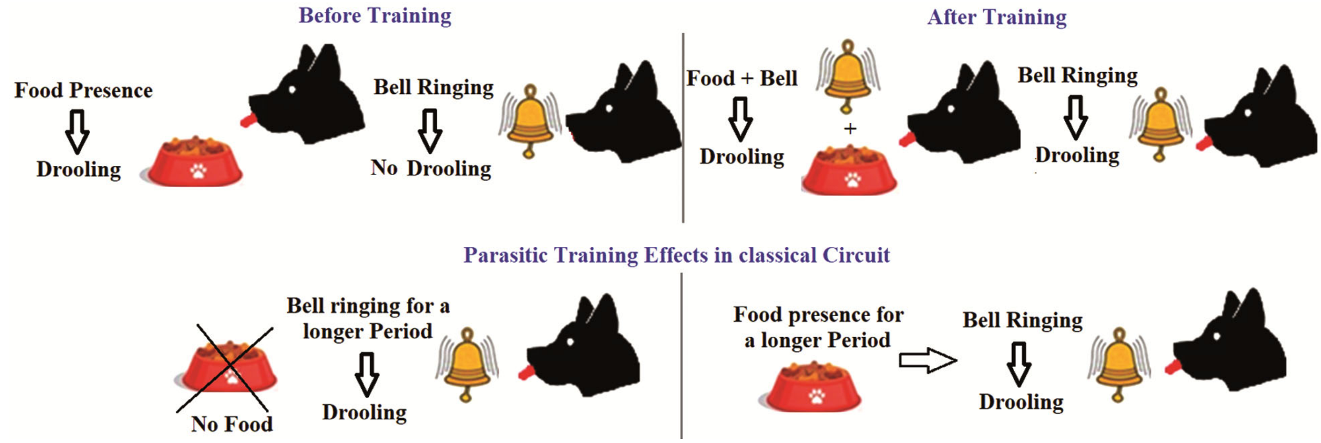

Fig. 1 — Schematic diagram showing the associative learning phenomena observed in a dog

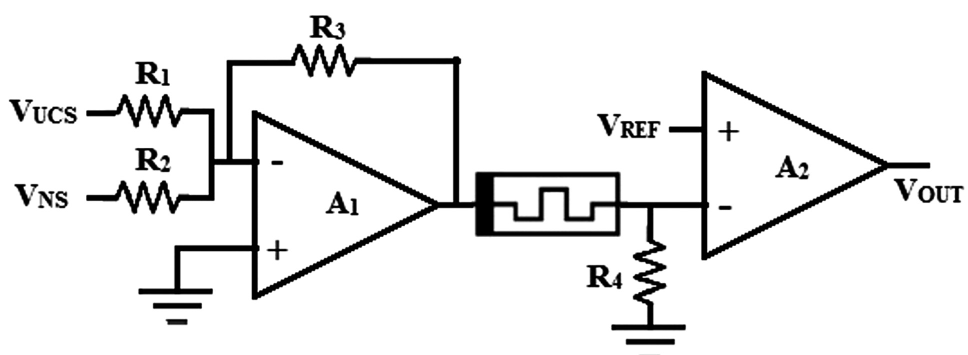

Fig. 2 — The dual Op-Amp circuit based on memristor reported in[23]

2.1 Classical Circuit to exhibit the Pavlovian's Learning

The classical circuit of Pavlov dog is shown in Fig. 2, which consist of two Op-Amps, four resistors, and a memristor. There are a number of benefits of using memristors in the classical associative learning circuit of Pavlov's dog, which are compactness, scalability, energy efficiency, and faster learning rates. The signals UCS and NS, in their high states, respectively, indicate the presence of food and the ringing of the bell in front of the dog. The output of the circuit corresponds to the dog's drooling response.

This circuit offers a simple realistic model for observing the associative learning phenomena through electrical signals. The circuit can be explored to find its application in autonomous vehicles and robotics etc. But this circuit have some issues which have been discussed in the simulation results section. As per simulation results of this classical circuit, the Pavlov dog sometimes drools without presenting food when the bell rings or the output is generated for the bell without together appearance of the food and bell signal i.e. without proper training.

2.2 Applied model of the HP Memristor

A memristor is an electronic component that regulates and limits electrical current flow within a circuit while also recording the cumulative charge that has passed through it. Well-known mathematical models for memristors include the linear ion drift model[24], the Simmons tunnelling barrier model[25], the generalized model[26], the adaptive threshold model[27], and the voltage-threshold adaptive model[24]. However, these models fall short in capturing the synaptic-like behaviour of current memristive devices in artificial neural circuits. A metal-insulator-metal (MIM) made of two platinum electrodes sandwiched around a thin film layer of TiO2 produced a memristive response as shown in Fig. 2(a)[25]. Here, When W(t) = D, the resistance is denoted as R_{ON}, and when W(t) = 0, it is denoted as R_{OFF} as shown in Fig. 2(b)[26]. In this study, we applied a voltage-dependent threshold memristor model[29], mathematically defined as follows:

$$\frac{dw(t)}{dt} = \begin{cases} u_V \frac{R_{ON}}{D} \cdot \frac{i_{off}}{i(t)-i_o} f\big(w(t)\big), v(t) > V_{T+} > 0 \\ 0,\ V_{T-} \le v(t) \le V_{T+} \\ u_V \frac{R_{ON}}{D} \cdot \frac{i_{off}}{i(t)-i_o} f\big(w(t)\big), v(t) < V_{T-} < 0 \end{cases} \quad \ldots(1)$$

In Eq. (1), parameters i_{off}, i_0 and i_{on} are constants while $V_{T+,-}$ are the switching thresholds, u_v is the migration rate of the forming layer, while R_{ON} is the low-state resistance of the memristor and D denotes the size and $w(t)$ represents the width of the doped layer. As per[30], the nonlinear drift of the ions is expressed as;

$$f(w(t)) = 1 - \left(\frac{2w(t)}{D} - 1\right)^{2p} \quad \ldots(2)$$

A I/V plot obtained for the employed memristor model[31] has been mentioned in Fig. 3(c). It can be seen that it's a hysteresis plot with a pinch-off at origin signifying the inherent resistive memory property of the device.

3 Proposed Improvement over the Existing Circuit

To overcome the limitations such as parasitic training effects i.e. inability to differentiate the food and bell signal of classical conditioning circuit, we have proposed a revision in the classical circuit as discussed in Fig. 4. It consists of two OR gate, one AND gate, one comparator, SR-latch using two NOR gate, three resistors and one memristor. The CMOS implementation of proposed circuit is designed using fifteen PMOS, fifteen NMOS, three resistors and one memristor as shown in Fig. 5. In this proposed circuit, integrating memristor with CMOS technology is essential for creating hybrid circuits that combine the advantages of both technologies. It offers a range of advantages that combine the strengths of both technologies, enabling new possibilities for efficient, high-performance, and scalable computing systems. Simulation results of both classical circuit and the proposed circuit are discussed in next section.

The circuit implements an associative learning system using logic gates, a memristor, a comparator, and a latch to mimic Pavlovian conditioning as shown in Fig. 4. The first AND gate detects when both input signals, V_{UCS} (food stimulus) and V_{NS} (neutral stimulus, e.g., bell), are present simultaneously, triggering a change in the memristor's resistance (M). The voltage across the memristor, determined by Ohm's Law ($V_M = I_M \times R_M$), is compared with a reference voltage V_{REF} in the comparator. If V_M exceeds V_{REF}, the comparator output activates the latch, which holds the learned state even when V_{UCS} is removed, ensuring that V_{OUT} remains high when only V_{NS} is applied later. The second AND gate ensures that the output is triggered only when the learned association has been formed, while the OR gate stabilizes the response by allowing either the learned signal or direct stimulus to activate the output. The system thus modifies the memristor's resistance over time ($\Delta R_M/\Delta t = f(V_M, I_M)$), enabling memory formation, with the RESET signal clearing the stored learning when required.

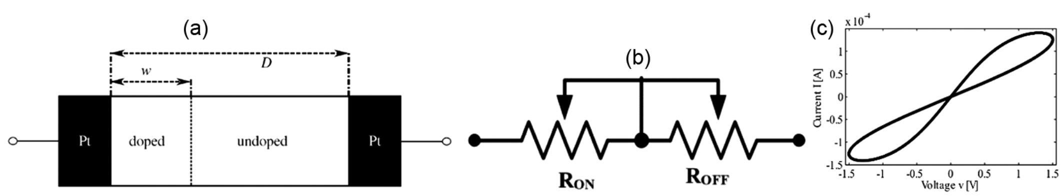

Fig. 3 — (a) HP Memristor model, (b) R_{ON}& R_{OFF} variation in HP Memristor, (c) Its PHL characteristic curve[25-31]

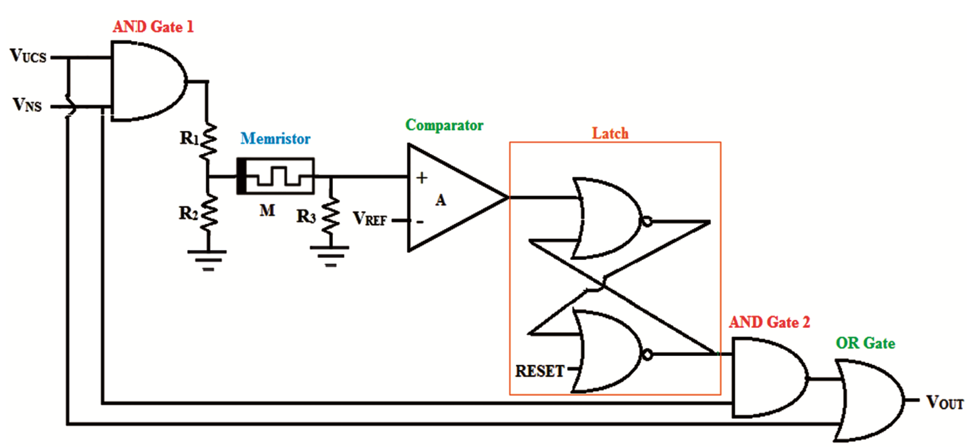

Fig. 4 — Proposed improved Pavlovian's learning Circuit

4 Simulation Result & Discussion

The PSPICE-generated simulation results are discussed in this section. First, we have simulated the classical circuit. Regarding simulation parameters, the resistor values were set as $R_1 = 500\ \Omega$; $R_2 = 1\ k\Omega$; $R_3 = 7.4\ k\Omega$ and $R_4 = 100\ k\Omega$. The memristor model[25] parameters were set as $R_{OFF} = 100\ k\Omega$ and $R_{ON} = 1\ k\Omega$ (which defines the range of possible resistance values of memristor). As V_{UNS} and V_{NS} stimulation signals, two voltage pulse sources with voltage levels of 0.2V and 0V (logical '1' and '0') were used. The period of these signals was set to 0.2 s for V_{NS} signal and 0.4 s for V_{UNS} signal.

For the proposed circuit simulations, resistance parameters were set as $R_1 = 320\ \Omega$; $R_2 = 1\ k\Omega$; and $R_3 = 100\ k\Omega$. The memristor model and stimulation pulse periods remained the same as for the classical circuit simulations. All logic gates used in the proposed circuit are for 3.3V logic; therefore, the input signals amplitude was set to 3.3V and 0V (for logical '1' and '0' respectively). Finally, since SR-latch is used in the simulated circuit, a RESET signal was activated to the high level for 0.1 s at the beginning of the simulation to ensure convergence and set circuit logic to the initial state.

4.1 Simulation Results for the Classical Circuit

The high state of the signals UCS and NS signifies the presence of food and the ringing of the bell in front of the dog, respectively. The circuit's output corresponds to the dog's drooling response. In Fig. 6(a), the simulation results depict scenarios where the high UCS signal represents multiple instances of food presentation. It is evident that the output remains consistently high for a high state of the UCS signal regardless of the NS signal's state. After several instances where both NS and UCS signals become high, the circuit begins to produce output even for the NS signal. This occurrence is attributed to the continuous signal occurrences, which cause

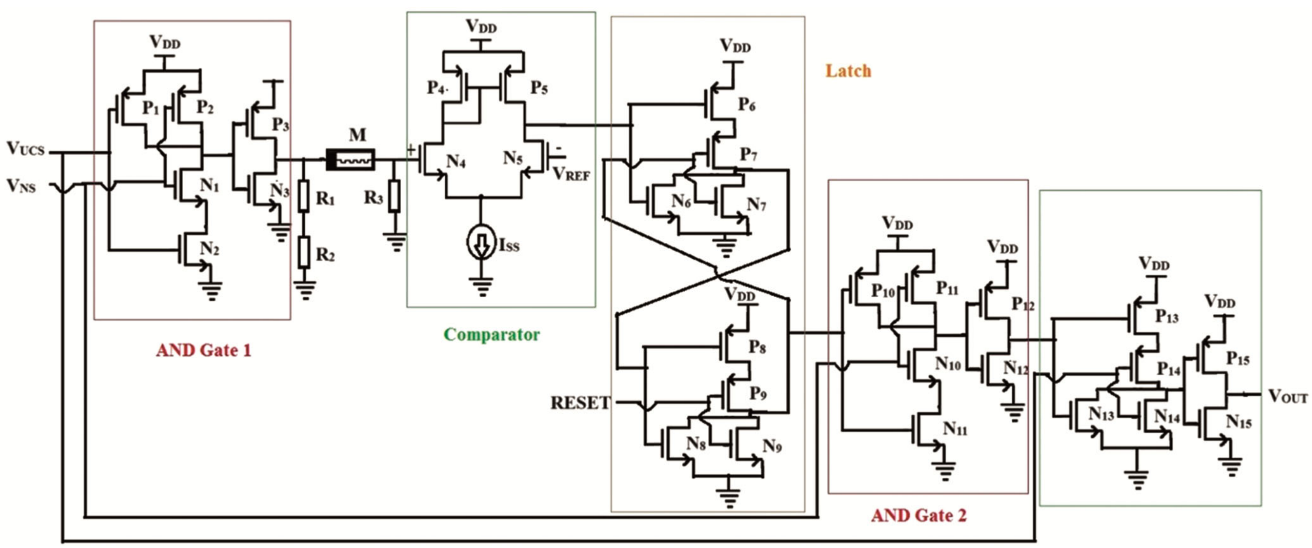

Fig. 5 — CMOS implementation of proposed improved Pavlovian's learning Circuit

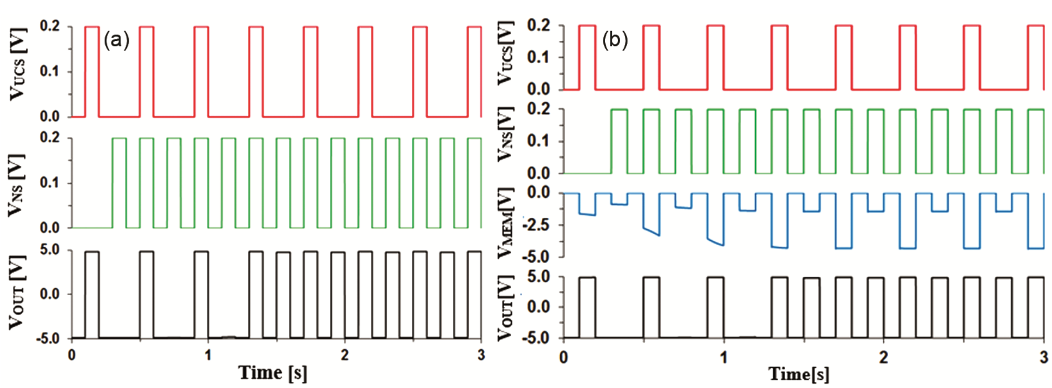

Fig. 6 — Simulation Results for the Classical Circuit shown in Fig. 2 describing the associative learning phenomena

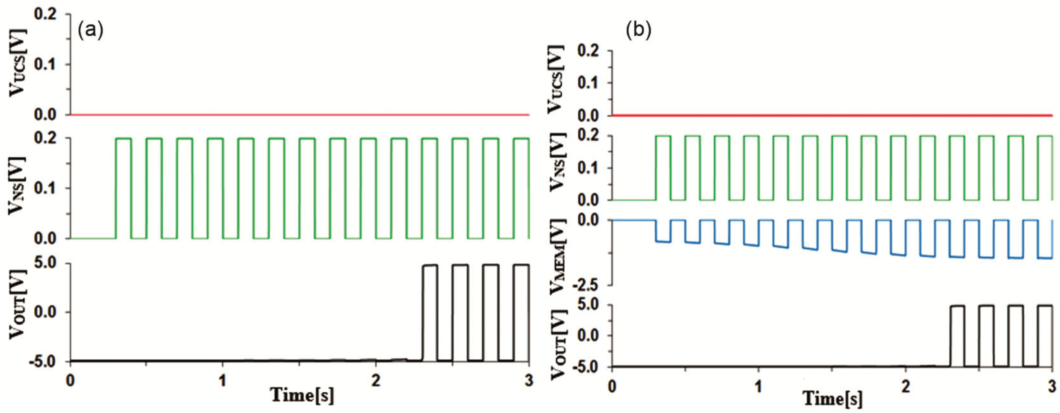

Fig. 7 — Simulation Results for the Classical Circuit showing the appearance of output V_{OUT} for ring signal without application of food signal

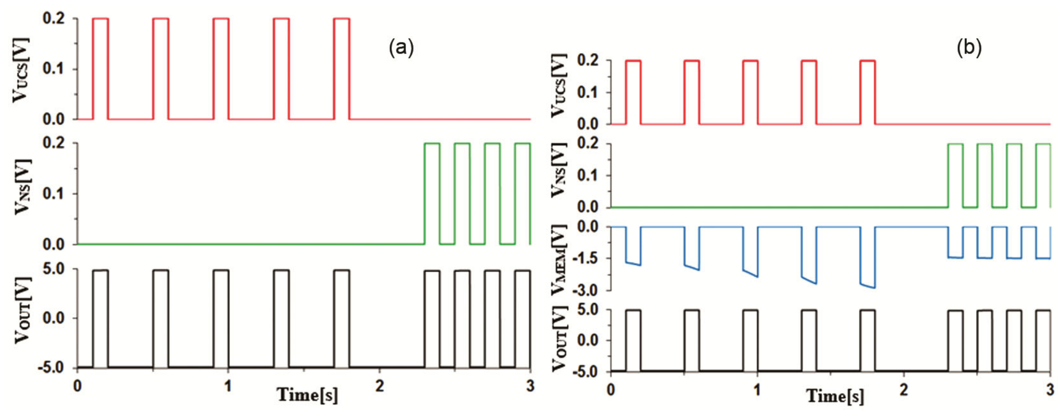

Fig. 8 — Simulation Results for the Classical Circuit demonstrating the appearance of the output without training i.e. no simultaneous occurrence of food and ring signal

the memristance to decrease to a level where the comparator starts providing output even for the NS signal. The evidence of this can be observed in Fig. 6(b).

According to Fig. 6, the designed circuit appears to fully emulate the function of associative learning. However, upon closer examination, it is discovered that if the ring signal (NS) is presented without stimulating the UCS line, the output occurs after some instances (as depicted in Fig. 7(a). This is because the NS signal alone is sufficient to decrease the memristance of the memristor and elevate the compactor input above the reference voltage. It's akin to a dog starting to drool immediately after the bell rings. Additionally, in Fig. 8(a), it can be observed that even without presenting the food and ring together, a training fallacy is observed. After several pulses of the V_{UCS} signal with NS being zero, the output also begins to occur for the NS signal with a UCS signal of zero.

4.2 Simulation Results of the Proposed Circuit

The simulation outcomes have been generated to demonstrate the associative learning capability of the modified proposed circuit as depicted in Fig.5. Table. 1 describing the aspect ratios of the transistors (NMOS and PMOS) used in proposed circuit. The simulation data illustrated in Fig. 9(a) & 8(b) directly simulate the associative learning phenomena observed in canines. These results were previously depicted in the circuit diagram shown in Fig.3. However, what distinguishes this redesigned circuit from its predecessor is its enhanced ability to precisely differentiate between the food and ring signals, as well as their simultaneous occurrences. As evident in Fig. 10 (a & b), the output remains zero for the V_{NS} signal, unlike in Fig. 7, as the circuit has not undergone training. Similarly, in Fig. 11, it can be observed that the output is never generated as long as the UCS signal remains zero, regardless of the frequency of V_{NS} signal occurrences.

Table 1 — Aspect Ratios of the Transistors used in Proposed Circuit given in Fig. 5

Parameters	Values
NMOS Transistors (W/L)- (N_1, N_2, N_3, N_4, N_5, N_6, N_7, N_8, N_9, N_{10}, N_{11}, N_{12}, N_{13}, N_{14} & N_{15})	3.6/0.36 (μm/μm)
PMOS Transistors (W/L)-(P_1, P_2, P_3, P_4, P_5, P_6, P_7, P_8, P_9, P_{10}, P_{11}, P_{12}, P_{13}, P_{14} & P_{15})	7.2/0.36 (μm/μm)

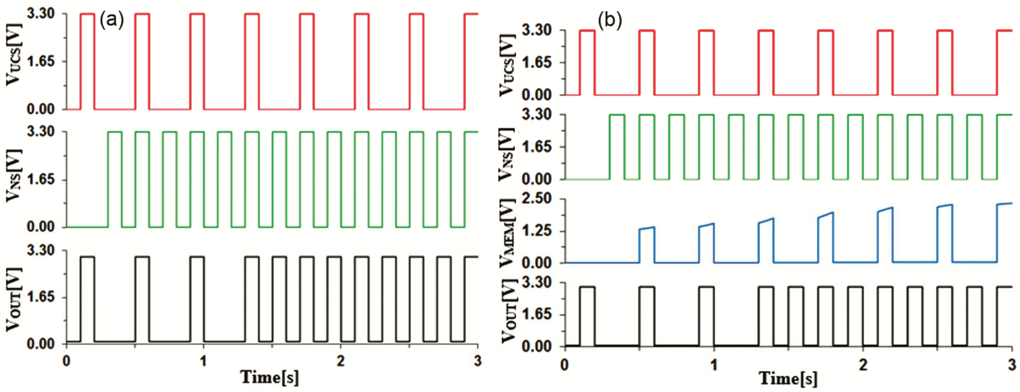

Fig. 9 — Simulation results of the proposed circuit demonstrating the associative learning behavior through electrical signals

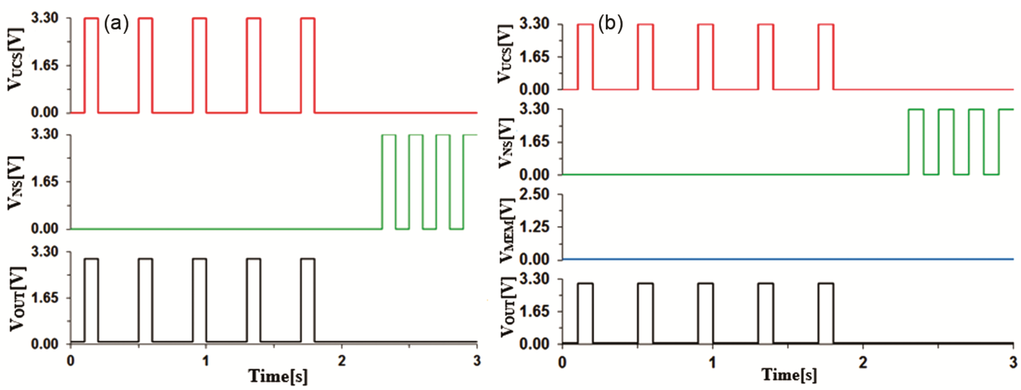

Fig. 10 — Transient curves showing the response of the proposed circuit demonstrating no output without training

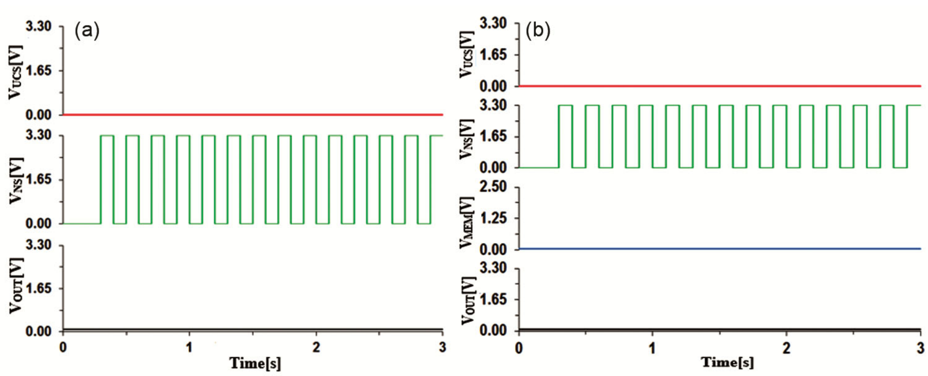

Fig. 11 — Transient response of the proposed circuit demonstrating no output for prolonged application of bell signal without food signal

5 Conclusion

Use of memristor in developing neuromorphic circuits has been a trend in this decade. By leveraging the unique properties of memristors and CMOS, researchers can develop more robust, scalable, and efficient neuromorphic systems. This work adds an important design in the existing research repertoire and is mainly focused on resolving the limitations of classical circuit of pavlovian's associative learning. These limitations might result in inapplicability of the classical conditioning circuit in such real-time cases where the sequence of inputs coming to the associative learning system is not fixed. And consequently, the circuit can result in unwanted indication signals. Above issue is resolved by our proposed circuit based on memristors and few digital components along with Op-Amps. The dog's drooling reaction corresponds with the circuit's output and the circuit gets rid of parasitic training effects. The Pavlov's learning circuit has applications beyond modeling a dog's behavior, particularly in neuromorphic computing, adaptive robotics, and AI hardware for pattern recognition and decision-making. It is also useful in biomedical signal processing and sensor fusion systems for intelligent response generation. In this paper, we are used PSPICE 0.18 µm with CMOS technology for obtaining simulation results that are compatible with concept of the associative learning.

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