Analysis of Multilayer Perceptron with Rectifier Linear Unit Activation Function

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Abstract—The implementation of analog neural network and online analog learning circuits based on memristive crossbar has been intensively explored in the recent years. The design of various activation functions is important for neuromorphic circuits and systems, especially deep leaning neural networks. There are several implementations of sigmoid and tangent activation function, while the analog hardware implementation of the neural networks with linear activation functions is an open problem. Therefore, this paper introduces a multilayer perceptron design with linear activation function using TSMC 130 nm CMOS technology. In this paper, the performance of the proposed linear activation function is illustrated. In addition, the temperature variation and noise analysis are shown.

Index Terms—Linear Activation Function, Multilayer perceptron, Crossbar, Memristor

I. INTRODUCTION

The discovery of the memristive elements lead to the possibility to implement various neural networks on hardware [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11]. There are several recent works that illustrate the implementation of analog activation functions for neural networks [12], [8], [2], [13], [4]. Most of the works illustrate implementation of basic perceptron based neural networks with sigmoid and tangent activation functions [12], [8], while the possibility of neural network with other activation functions is not explored.

In this paper, we propose the implementation of the basic perceptron neural network with linear activation function. We provide a basic information about the performance of the memristor and show the simulation of the memristor behavior. By applying different amplitude of voltage desired resistance can be obtained. Below threshold voltage memristor acts like a simple resistor with it last set resistance. During simulations, memristor was set to different resistance such as 40, 17 kΩ. Based on the performance of the memristor, we implement the programming cells of the 2x2 crossbar array and build a simple perceptron network with linear activation function circuit. Temperature and noise analysis were performed on perceptron circuit. The advantages of memristor-based circuit in terms of area and power dissipation are discussed.

II. MEMRISTOR MODEL

This section provides some background information on memristor along with its simulation, and it provides some discussion on different operating ranges of simple memristor circuit.

A. What is memristor?

Three basic two terminal components, namely, resistor, capacitor and inductor, are related with four fundamental variables: voltage, current, charge, and flux[14]. The fourth component known as memristor, introduces relation between charge and flux, \( d\phi = Mdq \), where \( M \) is defined as memristance [15], [16], [17], [18]. The name memristor(memory resistor) is chosen because resistance of the memristor defined by the history of current passing through it [14], [19], [20].

B. Memristor simulation

AC supply voltage is applied to memristor to analyze memristor behavior. Memristor has its threshold voltage below which operating resistance does not change[14]. In practice, different characteristic curves were obtained by altering the amplitude of voltage supply. Initial resistance of memristor was set to 50 kΩ.

C. Results

It is noticed that memristor shows two different behaviors depending on variable voltage. As can be seen from Fig. 2, for some values of voltage, current changes linearly and has non-linear behavior in some regions. This can be explained by the equations (1) and (2) given in report[15]. This means that above threshold voltage memristor resistance changes non-linearly.

\[
 v(t) = \left( R_{on} \frac{w(t)}{D} + R_{off}(1 - \frac{w(t)}{D}) \right) \\
 \frac{dw(t)}{dt} = \mu_v R_{mn} \frac{q(t)}{D} 
\]

where \( \mu_v \) is a mobility.

Further analysis of memristor show that as the input voltage increases, current curve gets non-linear. In Fig. 3, four different
current curves are plotted. One which has sharpest change correspond to 1.5 volt input and means that higher the amplitude of input voltage sharper the change in resistance.

As can be seen from the Fig. 4, it is clear that threshold voltage is 1V and above this point I-V curve is non-linear. Below 1V, two straight lines are obtained. Line with larger gradient represents ON state of the memristor. Similarly, second line represent OFF state as the resistance is high and current passing through the memristor is low.

By applying right duration or amplitude of pulse as mentioned before, desired resistance can be obtained. The formula for resistance estimation can be found in sub file of memristor given in appendix which is used in [21], [22] and discussed in report [22]. Fig. 5 exactly labels the change on resistance of the memristor in terms of voltage amplitude across the memristor. All pulses have duration of 0.2s. Knowing that $R_{off}$ and $R_{on}$ are 62 and 3 kΩ respectively following table I was drawn.

| Voltage amplitude, V | Obtained resistance, kΩ |
|---------------------|-------------------------|
| 1                   | Remains the same         |
| 1.4                 | 17                      |
| 2                   | 3                       |
| 2.5                 | 3                       |

TABLE I

Resistance programming with input voltage

III. MULTI LAYER PERCEPTRON

Perceptron, also termed as single layer perceptron, is a simple artificial (hardware or software) model of biological neuron and synapses. The idea of perceptron is to give single analog or binary output based on several analog or binary inputs [23].

A. Crossbar Array

Crossbar array could be used as a single or multi layer perceptron depending on its dimension. For example, 2x2 and 3x3 arrays correspond to two and three layer perceptrons, respectively. In Fig. 7 2x2 crossbar array is shown. Each column represents a layer and memristors play a role of weighted links(synapses).

In crossbar array write and read operations can be implemented. So the perceptron can be trained with the feedback system. To write on chosen cell voltage applied to desired column and corresponding ground should be grounded. Side effect of write operation is that extra current flows appear on other cells. For example Figs. 7 and 8 show regulated memristor with blue color and unwanted current flowing through memristors M2 and M3 labeled with red.

Furthermore, in Fig. 9, 3x3 crossbar array shown with chosen cell which is programmed and cells with extra current...
labelled with red. Extra current in red dots shown in figures can cause noise errors and lead to extra power consumption. Possible solutions of this problem are given in [24] with adding MOSFETS or diodes. After the resistance of each memristor is set until last, Information(resistance) is read applying voltage below threshold. In Figs. 10 and 11 the same behavior as for single memristor can be noticed for the resistance of memristor which is being programmed. Fig. 12 shows current flow in each of the memristor in 2x2 crossbar array. If voltage below threshold is applied, $V/50k\Omega$ should flow through the memristor.

### B. Rectifier Linear activation function

It was mentioned earlier that perceptron has its current summator and activation function. Circuit for the activation function is shown in Fig. 13. Diode is added to the output of the opamp to cut the negative current flow in the circuit. Output characteristic of activation function can be observed from Fig. 15. It is clear from figure that output voltage linear dependent on input voltage and has oV output at negative input as it was desired. The circuit in Fig. 13 is also knowns as superdiode.

### C. Temperature analysis

Temperature analysis were performed in LTspice for both crossbar array and activation function. During the test between -50 and 50°C any significant change in characteristic curves was noticed. Temperature change had effect only in 2-3 pA range and is hard to differentiate from the graph. This means that, introduced circuit of perceptron has durability to temperature change.

### D. Noise analysis and error

Noise test was performed in LTspice and from Fig. 15, it clearly seen that error due to the noise increases as operating frequency increases. Also, it is noted that after 100Hz error distribution gets saturated. In addition, error during write operation of crossbar array increases by the number of write cycles. According to [25], error increases slowly until 50th cycle, then sharply decreases along with the number of cycles is increased further. Also [25] state that, it is difficult to realise 16x16 crossbar array as it has significant error values.

### E. Area calculation

Memristor is promising device in terms of its size. Nowadays, 1 mosfet transistor occupy the same area as 8 memristors[26]. Investigation done by [24] state that, memristor based memory cells have density 3 times greater than its closest opponent, flash memory. It is 154Gbit.sec for memristor based circuits and 52 for traditional flash memory.
In size, again, memristor based memory cells are two times smaller than flash memory where transistors are used.

IV. CONCLUSION

The study presents deep explanation of memristor simulation which is hardly implemented in memristor based crossbar array. Temperature analysis state that perceptron analyzed in this study has good performance and potential. Noise analysis higher than 100Hz show constant error for any frequency meaning that circuit is durable to noise too. In terms of area memristor has huge advantage over MOSFETs. Small are use can lead to reduced power consumptions.

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Second International Conference on Computing and Network Communications (CoCoNet’18)
Fig. 15. Noise ration of activation function circuit

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