Neuromorphic Circuits With Neural Modulation Enhancing the Information Content of Neural Signaling

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ABSTRACT

Biological neurons signal each other in a rich and complex manner to perform complex cognitive computing tasks in real-time. The implementation of such capabilities using electronic circuits is a difficult task. Many neuromorphic circuits mimic different aspects of a biological neuron, yet neural modulation has received little focus. Modulation is a key aspect of understanding how neuron processes and interprets information. We posit that each neuron may have a unique built-in modulation function depending on its role. To build rich behavioral neurons, this paper introduces a new technique capable of converting continuous stimulus shapes into modulated spiking/bursting patterns. We test the hypotheses using the simplest modulation function (direct correlation). The results show plausible excitatory spiking patterns consistent with the Izhikevich mathematical model. Implementation of circuits was conducted using the 45nm CMOS technology node, and functional verification is discussed in detail using Cadence Virtuoso Simulator tools.

CCS CONCEPTS

• **Hardware** → **Neural systems; Integrated circuits; Analog and mixed-signal circuits.**

KEYWORDS

Neuromorphic silicon neuron, simple spiking model, neuromorphic systems, neuromorphic computing

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1 INTRODUCTION

Neuromorphic systems rely on very large-scale integration (VLSI) of interconnected electronic devices, which allows these systems

to resemble various biological neural mechanisms [18]. Such systems are fault-tolerant and usually follow a distributed memory-computational architecture using different synaptic weights [19]. We and many others have shown various electronic implementations of neurons, synapses, and other related mechanisms [16, 20, 21, 29, 41].

Our previous neuromorphic circuits for the Biomimetic Real-time Cortex (BioRC) have demonstrated capabilities such as the implementation of spike-timing-dependent plasticity to mimic learning mechanisms in biological neurons [24], learning without forgetting [42], using dopamine signaling as a reward in learning [2], spiking with a particular set of inputs [28], and recently, spiking in response to specific frequencies [43]. With the library of neuromorphic circuits that we have implemented and as part of our investigation of how the human brain might learn new tasks without forgetting old ones, we have begun to examine neural signaling and how different patterns may convey different information.

The most widely accepted neural computation scheme views neurons as a centralized unit at which an action potential (AP) takes place if the summation of the synaptic input at the soma exceeds a certain threshold, whether the summation is performed linearly or non-linearly (current or conductance based, respectively) [3]. However, in 2017, Sardi et al. conducted an experiment to conclude that a biological neuron consists of multiple independent threshold units [36]. Motivated by the realizations described in [36], we built an electronic neuron consisting of two dendritic branches, to encode information about the origin of the stimulus by observing the variability of the repolarization time of a single spike [28].

This paper introduces a CMOS neuromorphic model capable of encoding different stimulus shapes into different spiking/bursting patterns. We show that the generated patterns are consistent with the Izhikevich plausible patterns [22]. The modeling hypothesis suggests that the influence of stimulus dynamics on the induced APs may follow an unknown type of neural modulation. Here, the term *neural modulation* refers to the process by which a neuron translates its synaptic inputs to specific AP pattern. Although such modulation has not been well discussed in the literature, a biological basis is proposed in [8].

The proposed model can be used in building a rich behavioral neuromorphic neuron to perform complex tasks. Figure 1 shows the general block diagram of the proposed model. To investigate the behavioral capabilities, (1) we modeled the output of various dendritic computations using the parameter V_{soma} , in which V_{soma} can be any analog or digital signal, and (2) a direct correlation is used between V_{soma} and the AIS modulation block. A direct correlation means there is no modulation function, hence the modulation

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function is shown as a dashed box (Figure 1), to show that even with the simplest type of modulation, the neural computation can be increased, although other types of modulation function can be used to perform neural arithmetic operations (e.g. differentiation or integration). We demonstrate the circuit using Cadence Virtuoso Simulator Tools.

Figure 1: The general block diagram of the proposed neuron model.

2 THE MODEL

2.1 Related Biological Background

Action potentials are initiated (sudden rise) in the region between the soma and the axon hillock, which called Axon Initial Segment (AIS) [30, 34], and propagate reliably through the axon hillock [38]. Recent studies have suggested that the function of the AIS may not be limited to the generation of APs, but includes dynamic signal processing [26]. From the neuromorphic point of view, AIS can be thought of as a processing unit within a neuron to translate the somatodendritic oscillations into APs, whereas the axon hillock can be modeled as a reliable transmission cable with multiple repeaters (nodes of Ranvier).

There are several reasons for the AP generation at the AIS. First, the AIS diameter is an order of magnitude smaller than the soma, which implies a smaller characteristic capacitance; thus, a less inward current is required to provoke APs [26]. Second, there is a higher density of voltage-gated ion channels compared to the soma. The voltage-gated ion channels reported at the AIS site include voltage-gated Sodium channels (N_{av}) and voltage-gated Potassium channels (K_v). The N_{av} channels contribute to lowering the neural threshold, and consequently, increase excitability, whereas K_v channels play a significant role in shaping APs due to their lower threshold activation and shunting properties (repolarization of APs) [23, 25].

Structurally, the length and location (relative to the soma) of the AIS vary with neural activities [11]. With such variations, neurons can adapt to particular frequencies during sound localization processes [27]. Moreover, in cortical and hippocampal regions, the AIS of the excitatory neurons allows axo-axenic cells (a specialized type of GABAergic interneuron) to directly modulate the APs [15, 40], and synchronize neural activities [5].

On the other hand, the intracellular Ca^{+2} mechanism plays a significant role in neural signaling, where this mechanism increases the neural firing rate (bursts' generation) [37]. Bursting APs can be generated externally throughout a network of neurons to generate rhythmic motor patterns [9], such as the neurons found in the central pattern generator (CPG) [32], or intrinsically using voltage gated Calcium channels (C_{av}). In general, C_{av} channels can be categorized into high-voltage (HVA) and low-voltage (LVA) activated

channels based on the threshold activation voltage. The activation of HVA channels, such as T-type Ca^{+2} channels, during small cell depolarization causes a more substantial cell depolarization at which both C_{av} and N_{av} channels become activated, which result in the generation of bursting APs [7].

In the cortical region, Pyramidal Neurons (PNs) comprise most of the neural population and have interesting neural behaviors. Layer 5 pyramidal neurons (L5-PN), for example, are the only known type of neurons that can reach all six layers of the cortex, making them one of the primary cortical integrators [12, 37]. Based on their intrinsic firing properties, L5-PNs are classified into low-frequency spiking neurons and high-frequency bursting neurons [6, 10, 33]. However, under certain circumstances, such as the dendritic morphology [31, 39], and voltage-gated Calcium channel (C_{av}) distribution [4], individual PNs can produce regular and burst spiking patterns [7]. In addition, recent studies have revealed that individual L5-PN can adapt both regular and burst spiking patterns repetitively at different thermal stimuli [13].

2.2 Neuromorphic Implementation

The proposed model is a modified version of our previous voltage-based axon hillock design [16], to support dynamic activation-deactivation of C_{av} channels and a direct stimulus to AP modulation. The model's schematic diagram consists of *Somatodendritic*, *Amp*, *Cav*, *Spiking Generator*, and *AISModulation* sub-blocks, shown in Figure 2 with different colors.

In Figure 2, the *Somatodendritic* sub-block models the threshold variabilities and provides information about the dendritic Calcium ion concentration. *Amp* is a controlled amplification stage to provide variable gain for the subsequent sub-blocks. C_{av} models the effect of the voltage-gated Calcium ion channels through bursting. *Spiking Generator*, K_v , and N_{av} sub-blocks are adopted from Hsu's model in which *Spiking Generator* uses gated cross-coupled inverters to model the spike initiation mechanisms, K_v models voltage-gated Potassium ion channels, and N_{av} models voltage-gated Sodium ion channels. *AISModulation* sub-block models the AIS signal processing, by correlating stimulus dynamic into specific AP patterns.

Moreover, there are seven parameters to provide a wide range of variability in modulating and shaping the APs:

Figure 2: The Schematic diagram of the proposed neuron model in which INV1 is a single stage CMOS inverter, and COMP1, COMP2, COMP3 are low power differential-based comparators. To simplify the schematic connections, the dashed and the solid connections are used interchangeably.

- The parameter V_{soma} models the output of the dendritic computations to be used as an input to the proposed model, while parameter V_{soma_Thre} models the threshold variability to dynamically control neural activities. Hence, the sensitivity of detecting smaller V_{soma} potentials is inversely proportional to the value of V_{soma_Thre} .
- The parameter Ca^{++} designates the dendritic Ca^{+2} ion concentration, whereas the parameter $CaThre$ models the dynamic threshold activation of Ca_v channels.
- The parameter $Adapt$ controls the current flow through M16 (Threshold-Calcium current [17]) when the Ca^{+2} ion channel is opened (M17 is turned on); hence, regulating the maximum burst width. However, when the Ca^{+2} ion channel is closed (M17 is turned off), $Adapt$ controls the frequency of spikes through M19.
- The parameters N_a+ and $K+$ represent the Sodium ion concentration and the Potassium ion concentration at the AIS, respectively, whereas C_A models the AIS capacitance.

Figure 3: The schematic diagram of the comparators.

In addition, the model consists of three low power differential-based comparators ($COMP1$, $COMP2$, and $COMP3$). $COMP1$ models threshold variabilities by comparing V_{soma} and V_{soma_Thre} , $COMP2$ monitors dendritic Ca^{+2} concentrations and consequently activates/deactivates Ca_v channels, and $COMP3$ permits action potentials based on stimulus shapes. The comparators' schematic diagram is shown in Figure 3, in which $in+$ and $in-$ are the comparators' positive and negative input terminals, respectively. The output from the differential pair amplifier is followed by two cascaded inverters to digitize the output voltage swing into logic "1" for ($\Delta in > 0$) and logic "0" for ($\Delta in < 0$) where $\Delta in = (in+) - (in-)$.

In other words, $COMP1$ outputs a logic "1" when the membrane potential exceeds a certain threshold ($V_{soma} > V_{soma_Thre}$) and outputs logic "0" when $V_{soma} < V_{soma_Thre}$. Similarly, in modeling Ca_v channels, $COMP2$ outputs a logic "1" when the dendritic Ca^{+2} concentration exceeds the Ca_v threshold activation voltage ($Ca^{++} > CaThre$), and outputs logic "0" when $Ca^{++} < CaThre$ to deactivate Ca_v channels. As a result, AP patterns can be classified into bursting APs if $COMP2$ exhibits logic "1" and spiking APs otherwise. Likewise, $COMP3$ compares V_{soma} and V_{CA} (voltage across capacitor C_A). Consequently, $COMP3$ outputs a logic "1" when $V_{CA} > V_{soma}$, to inhibit the generation of APs by activating transistor M15, and a logic "0" when $V_{CA} < V_{soma}$ to allow APs depolarization. Comparing V_{CA} and V_{soma} using $COMP3$ allows a direct AP modulation. In other words, the initiated AP depends on

the shape of V_{soma} . Such dependency leads to continuous generation of various spiking/bursting patterns.

3 VARIOUS SPIKING AND BURSTING PATTERNS

3.1 Converting Dynamic Stimulus to APs

In this section, we simulate the model's schematic diagram shown in Figure 2, using Cadence Virtuoso Simulator Tools to show that various spiking patterns can be generated continuously as a function of ion channels (N_a+ , $K+$, Ca^{++}), $Adapt$, and dynamic V_{soma} shapes. However, to simplify the analysis, throughout this paper, N_a+ and $K+$ are set to be 900mV and 0V, respectively. The contribution of the ion channels in shaping APs is summarized in the sketch illustration of both single and burst AP patterns shown in Figure 4(A), in which N_a+ sets the peak spike/burst amplitude, $K+$ sets the spike/burst resting potential, and the difference between Ca^{++} and $CaThre$ defines the mode of APs (bursting or spiking mode). The current states (conditions) of ion channels, $Adapt$, and V_{soma} required for generating a specific pattern, are outlined in Figure 4(B) for regular spikes (RS), phasic spikes (PS), tonic bursts (TB), single burst per stimulus (SB), class-1 spikes (CS1), subthreshold oscillation (OSC), depolarization after potential (DAP), integrator spikes (INT), and mixed mode (MIX) patterns.

In Figure 4(B), when two or more patterns have the same setup conditions, such as (RS, INT, CS1, OSC) and (TB, SB) patterns, switching between patterns depends solely on the dynamic shapes of V_{soma} . For example, the generation of both SB and TB patterns requires $Adapt > V_{dd}/2$, $Ca^{++} > CaThre$, and $K+ = 0$, hence, the selection between SB and TB patterns depends on the dynamic shape of V_{soma} . Similarly, the generation of RS, INT, CS1, and OSC patterns requires $Adapt > V_{dd}/2$, $Ca^{++} < CaThre$, and $K+ = 0$, thus, the selection between RS, INT, CS1, and OSC patterns depends on the shape of V_{soma} .

Figure 4: A sketch illustration of spike and burst APs showing the model's voltage-gated ion channels contribution in shaping APs, (A). (B) shows the model's conditions associated with the generation of single burst (SB), tonic bursts (TB), regular spikes (RS), integrator spikes (INT), class-1 spikes (CS1), subthreshold oscillation (OSC), phasic spikes (PS), phasic spike with depolarization after potential (PS-DAP), regular spikes with depolarization after potentials (RS-DAP), and mixed mode (MIX)

The simulation results of the model's schematic diagram for the previously mentioned spiking/bursting patterns are shown in Figure 5 using similar stimulus shapes of V_{soma} presented in the Izhikevich mathematical model [22]. To discuss how individual

Figure 5: The relationship between various V_{soma} shapes and their corresponding action potentials for (A) regular spikes, (B) phasic spikes, (C) tonic bursts, (D) single burst per stimulus, (E) class-1 excitable, (F) subthreshold oscillations, (G) depolarization after potential, (H) integrator, and (I) Mixed mode.

pattern is formed, we group the results into three groups based on the generation conditions required for each pattern.

First, RS, INT, CS1, and OSC patterns are generated when $Ca++ < CaThre$ and $Adapt > V_{dd}/2$. The first is to inhibit bursting and permit spiking formation, and the second is to prevent current flow through transistors M19 and M20, forcing the current of M3 to flow only through M1. Since these patterns have the same conditions of generation, information about the stimuli is needed to identify which pattern the model should produce.

- The **RS** pattern shown in Figure 5(A) is generated using a constant voltage pulse of stimulus ($V_{soma} = 300\text{mV}$). The RS pattern frequency is directly proportional to the amplitude of V_{soma} (stimulus intensity).
- The **INT** pattern shown in Figure 5(H) corresponds to a train of short stimulus ($V_{soma} = 150\text{mV}$, and width = 4ns per pulse). Due to the accumulation of charges on capacitor C_A , the model is capable of detecting consecutive rapid events ($T_1 = 6\text{ns}$). In contrast, when the time between consecutive stimulus increases ($T_2 = 26\text{ns}$), the model becomes less excitable due to the loss of the accumulated charges on C_A .

- The **CS1** pattern shown in Figure 5(E) resembles a ramp-like stimulus shape ($V_{soma} = 800\text{mV}$, with rising time $t_r = 60\text{ns}$). The result is consistent with the generated RS pattern, at which the frequency of spikes is proportional to the amplitude of V_{soma} .
- The **OSC** pattern shown in Figure 5(F) takes place when $V_{soma} = 100\text{mV}$ at which C_A experiences multiple charging and discharging phases due to the small stimulus amplitudes. However, when introducing further stimuli ($V_{soma} = 200\text{mV}$ and width = 8ns per pulse), the model exhibits spikes. This might be important for detecting small perturbations of stimuli.

Second, TB and SB patterns are formed when $Ca++ > CaThre$ and $Adapt > V_{dd}/2$. When $Ca++ > CaThre$, the output of *COMP2* sets the gate voltage of M17 to V_{dd} ; Consequently, transistor M17 is switched on, allowing the current to flow from M4 through M16 and M17. Hence, reducing the gate voltage of M6 and M9 to a value near V_{th6} (the threshold voltage of M6). The current passing through M16 and M17 resembles T-current (low Threshold-Calcium current discussed in [17]). Therefore, at each rising edge of an individual intra-burst, transistor M6 operates in the subthreshold region while

M9 operates in the triode region. In contrast, at each falling edge of an individual intra-burst, M9 and M6 switch their operating regions where M9 operates in the subthreshold region, and M6 operates in the triode region. This continuous switching results in a consecutive generation of the intra-burst spikes.

Although the model relies on simulation results for extracting design parameters, the relation of the current as a function of the input gate voltage for M6 can be approximated using the drain-source current model (1) for the triode and (2) for the subthreshold operation regions. Similarly, for M9, by using μ_p , V_{SG} , V_{SD} , $|V_{thp}|$ instead of μ_n , V_{GS} , V_{DS} , V_{thn} , respectively.

$$I_{DS} = \mu_n C_{ox} \frac{W}{L} [(V_{GS} - V_{th})V_{DS} - \frac{V_{DS}^2}{2}] \quad (1)$$

$$I_{DS} = I_0 e^{\frac{V_{GS}}{nV_T}} \quad (2)$$

Where μ_n is the mobility of electrons, μ_p is the mobility of holes, C_{ox} is the oxide capacitance, W is the diffusion width, L is the diffusion length, V_{GS} is the gate-source voltage, V_{DS} is the drain-source voltage, I_0 is the characteristic leakage current, n is the subthreshold slope factor, and V_T is the thermal voltage.

- The **TB** pattern shown in Figure 5(C) corresponds to a constant input voltage pulse ($V_{soma} = 300\text{mV}$). The number of intra-burst spikes is proportional to the V_{soma} amplitude (stimulus intensity). In other words, the burst width increases as the V_{soma} amplitude increases. Thus, the **TB-Adapt** term is used to indicate tonic bursts with different widths as a function of dynamic V_{soma} amplitude (see section 4, Figure 7 for more details).
- The **SB** pattern shown in Figure 5(D) corresponds to two single bursts per stimulus. There are two scenarios for the generation of SB pattern; (1) when the width of stimulus is shorter than the time required for *COMP3* to turn transistor M15 on ($V_{soma} = 300\text{mV}$, and width = 2ns). (2) when the amplitude of stimulus is higher than the maximum voltage value across capacitor C_A ($V_{soma} = 700\text{mV}$, and width = 6ns).

Third, unlike the previously mentioned spiking patterns, DAP, PS, and MIX patterns have different setup conditions.

- The **DAP** pattern requires $Ca^{++} < CaThre$ and $K^+ > 0$. Since K^+ determines the resting potential voltage, the DAP pattern is directly proportional to K^+ . To generate the DAP pattern, other spiking patterns are required. Therefore, **PS-DAP** and **RS-DAP** are introduced to represent PS pattern and RS pattern with the DAP effect, respectively. Figure 5(G) shows RS pattern without DAP (leftmost three spikes) for $K^+ = 0$, and RS pattern with DAP (Rightmost three spikes), at which $K^+ = 900\text{mV}$.
- The **PS** pattern requires transistors M19 and M20 to be turned on so that M3 current can flow through M1, M19, and M20 to further decrease the gate voltage of M4, M2, and M18, see Figure 5(B). Therefore, the PS pattern requires $Ca^{++} < CaThre$ and $Adapt < V_{dd}/2$.
- The **MIX** pattern is generated using the dynamic activation/deactivation of C_{av} channels. In other words, the model produces bursting patterns when $Ca^{++} > CaThre$ and spiking patterns when $Ca^{++} < CaThre$, see Figure 5(I). In both

cases, the generation of mixed pattern requires $Adapt > V_{dd}/2$ to allow current flow through M16 and M17.

3.2 The Working Principles of The AIS Modulation Block

Understanding how the *AIS Modulation* sub-block converts dynamic stimulus into various spiking/bursting patterns requires a discussion of the relationship between V_{soma} and V_{CA} (the inputs of *COMP3*) is needed. Figure 6 represents the relationship between V_{soma} (red waveform) and V_{CA} (blue waveform) for all previously simulated patterns. In Figure 6, the relationship can be described using the relative refractory period (RRP), in other words, the time between two consecutive spikes/bursts.

The ideal RRP for spikes and bursts are denoted as RRP_s (green shaded region) and RRP_B (gray shaded region) in Figure 6, respectively, in which both RRP_s and RRP_B represent the period at which $V_{CA} > V_{soma}$. However, because switching from $V_{CA} > V_{soma}$ to $V_{CA} < V_{soma}$ using *COMP3* is not ideal (spontaneous switching), the model's propagation delay (T_d) is added (red shaded region) as shown in Figure 6. Thus, the actual relative refractory period can be extracted graphically from Figure 6 as ($RRP_s + T_d$) for spikes, and ($RRP_B + T_d$) for bursts patterns. During burst formation, capacitor C_A withstands multiple fast charging and discharging phases per burst, due to the formation of the intra-burst spikes, whereas during spike generation, capacitor C_A undergoes a single charging phase and a discharging phase per spike. Accordingly, RRP_B is smaller than RRP_s . However, since the value of T_d depends on the physical properties of the design, it remains the same for both spike and burst patterns.

Therefore, for the RS pattern (Figure 6(A)), as the amplitude of V_{soma} remains constant, the RRP_s remains the same for all subsequent spikes. For the PS pattern (Figure 6(B)), due to the activation of M19 and M20, the RRP_s is the largest compared to other patterns. In the TB pattern (Figure 6(C)), the RRP_B remains the same for all consecutive bursts due to the constant amplitude of V_{soma} . In the SB pattern (Figure 6(D)), the first stimulus represents the scenario where RRP_B is larger than the width of V_{soma} and the second stimulus represents the scenario at which $\Delta V > 0$ where $\Delta V = V_{soma} - V_{CA}$. For the CS1 (Figure 6(E)), the RRP_s is inversely proportional to the amplitude of V_{soma} ; in other words, $RRP_{S1} < RRP_{S7}$. For the OSC pattern (Figure 6(F)), the relationship between V_{soma} and V_{CA} is plotted in the logarithmic scale to show the voltage oscillation of V_{CA} . For the DAP pattern (Figure 6(G)), when $K^+ > 0$, the rightmost three spikes compared to the leftmost three spikes, have slightly larger V_{CA} ; hence, larger RRP_s . In the INT pattern (Figure 6(H)), the V_{CA} is higher for rapid occurring stimulus compared to slower stimulus. In the MIX pattern (Figure 6(I)), the value of V_{CA} is higher in the case of spiking compared to bursting; thus, $RRP_s > RRP_B$.

Analytically, the relationship between V_{soma} and V_{CA} can be approximated using the RC analysis at the positive terminal of *COMP3* in which the total capacitance (C_{tot}), the equivalent resistance for M11 (R_{11}), and the equivalent resistance for M12 (R_{12}) are shown in (3), (4), and (5), respectively.

$$C_{tot} = C_{g13} + C_A + C_{in} + C_{d11} + C_{d12} \quad (3)$$

Figure 6: The relationship between V_{soma} (Red) and V_{CA} (Blue) for all plausible patterns; (A) Regular spiking; (B) Phasic spiking; (C) Tonic bursting; (D) Single burst per stimulus; (E) Class-1 excitable spikes; (F) Subthreshold oscillations; (G) Depolarization after potential; (H) Integrator spiking; (I) Mixed mode. The ideal relative refractory period for spikes and bursts is RRP_s and RRP_B , respectively. T_d is the model's propagation delay.

$$R_{11} = 1/(\beta_{11}(V_{dd} - V_{thn})) \quad (4)$$

$$R_{12} = 1/(\beta_{12}(V_{dd} - |V_{thp}|)) \quad (5)$$

Where C_g is the gate capacitance; C_{in} is the input capacitance of *COMP3*; C_d is the drain capacitance; β_{12} and β_{11} are the beta effective of M12 and M11, respectively; V_{dd} is the DC supply voltage. Therefore, the discharging time (t_{dis}), and charging time (t_{ch}) can be approximated using (6) and (7), respectively.

$$t_{dis} = R_{11}C_{tot} \ln\left(\frac{V_{CA}(0)}{V_{soma}}\right), \text{ for } V_{CA} \geq V_{soma} \quad (6)$$

$$t_{ch} = R_{12}C_{tot} \ln\left(\frac{-V_{soma}}{V_{CA} - V_{soma}}\right), \text{ for } V_{CA} < V_{soma} \quad (7)$$

4 THRESHOLD VARIABILITY

Biological neurons have variable thresholds. This variability is inversely proportional to the APs rate [1, 14].

As Hsu has shown, the threshold for spiking can be modulated by the slope of V_{soma} , with spiking initiated earlier with faster V_{soma} rise [16]. Moreover, other factors, such as the mechanisms

of ion channels and synaptic properties, can alter neural threshold [35].

In the proposed model, both constant and variable thresholds can be modeled using *COMP1*. Figure 7 shows the simulated behaviors of the model's schematic using Cadence Virtuoso Simulator Tools at a fixed and dynamic neural threshold for $Na^+ = 900\text{mV}$, $K^+ = 0\text{V}$, and $CaThre = 300\text{mV}$.

Figure 7(A) shows the firing behaviors associated with a fixed neural threshold ($V_{soma_Thre} = 0\text{V}$). As a result, the model is capable of detecting all dynamic stimulus shapes since $V_{soma} > V_{soma_Thre}$. The output waveforms (AP1, AP2, and AP3) are generated at different conditions. In other words, the patterns within each of the output waveform, have the same setup conditions; thus, depending on the dynamic shapes of V_{soma} , various patterns are generated;

- AP1 is generated using $Ca^{++} < CaThre$ and $Adapt > V_{dd}/2$, where $Ca^{++} = 0\text{V}$ and $CaThre = 300\text{mV}$. The firing patterns include RS, OSC, INT, and CS1.
- AP2 is generated using variable Ca^{+2} concentrations ($Ca^{++} = [0, 500\text{mV}]$), and $Adapt > V_{dd}/2$. When $Ca^{++} > CaThre$

Figure 7: Shows the model behaviors for dynamic V_{soma} shapes. (A) represents different AP patterns at which $V_{soma} > V_{soma_Thre}$, and (B) shows AP patterns for the same V_{soma} variations, however, with a threshold variability (gray signal). AP1 and AP4 are generated at which $Ca^{++} < CaThre$ and $Adapt > V_{dd}/2$. AP2 and AP5 represent the outputs at which $Adapt > V_{dd}/2$ and $Ca^{++} = [0, 500mV]$. AP3 and AP6 exhibit PS spiking pattern where $Ca^{++} < CaThre$ and $Adapt < V_{dd}/2$. ZOOM2 and ZOOM5 are enlarged versions of the green shaded areas associated with AP2 and AP5 outputs, respectively.

the generated patterns include SB, TB, and TB-Adapt (denote bursts with various widths depending on the amplitude of the V_{soma}), whereas when $Ca^{++} < CaThre$, the resulting patterns of AP2 are the same as AP1.

- AP3 shows PS pattern where $Ca^{++} < CaThre$ and $Adapt < V_{dd}/2$. Here, $Ca^{++} = 0V$, $CaThre = 300mV$ and $Adapt = 0V$.

In contrast, Figure 7(B) shows similar V_{soma} shapes; however, with a dynamic variation of V_{soma_Thre} (gray signal). At $V_{soma} > V_{soma_Thre}$, the outputs of AP4, AP5, and AP6 are the same as AP1, AP2, and AP3, respectively, yet, when $V_{soma} < V_{soma_Thre}$, there are no permeable spiking/bursting APs. ZOOM2 and ZOOM5 are enlarged versions of the green shaded areas shown in the output of AP2, and AP5, respectively.

5 CONCLUSION

In this paper, a CMOS electronic model is proposed to emulate the rich, dynamic behaviors of biological neurons. We have shown through circuit simulations that by converting stimulus dynamics shapes (modeled using V_{soma}) into specific AP patterns, the model is capable of producing different AP patterns in real time, including regular spikes, phasic spikes, tonic bursts, single burst per stimulus, class-1 excitable spikes, subthreshold oscillations, depolarization after potential, integrator, and mixed mode. Moreover, we have shown how the model utilizes a dynamic threshold to mimic the biological neurons. The proposed model can be used to build a rich behavioral neuromorphic system capable of performing complex tasks.

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