CMP9783M – Neural computing

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Abstract:

This report examine the two neural computing systems using MATLAB - specifically, an Leaky Integrate-and-Fire (LIF) neuron with adaptation and a Hodgkin-Huxley (HH) model as an oscillator.The primary goal of these systems is to understand and simulate the dynamic behavior of these neuronal models, providing valuable insights into their complex electrochemical processes.In this study, MATLAB code is developed to execute the models with appropriate plotted graphs and a thorough discussion of the results is provided.

In section 1 matlab code is developed to simulates the impact of adaptation on the neuron's spiking behavior that includes the simulation of the neurons response to external stimuli,incorporating adaptation mechanism and analyze the result of the spiking patterns with plotted appropriate graphs

On the other hand in section 2 The Hodgkin-Huxley model is implemented to provide more detailed representation of the neurodynamics by considering the ion gated channels' conductances and external adaptive currents.matlab code is implemented to achieve the neuroscience goal to simulate the Type II properties of the Hodgkin-Huxley model.

This report aims to provide detailed and insightful exploration of the two mathematical neuroscience models implemented in matlab.

Introduction :

In this assessment the developer has implemented the two mathematical models to understand the intricate working of the neurons in the human brain. In this assessment two important models explored are the Leaky Integrate-and-Fire (LIF) neuron with adaptation and Hodgkin-Huxley model.

The Leaky Integrate-and-Fire (LIF) neuron model is a powerful model that captures the neuron's behaviors by incorporating an adaptive mechanism.Our aim is to observe the behavior of the neurons to the external adaptation currents over a periods of time and how the firing rate and membrane potential depends on the spikes.

On the other hand, The Hodgkin-Huxley model provides the dynamics of the action potential in the axon and the mathematical representation of the conductances in terms of activation and inactivation variables to model neurons.

This study attempts to uncover the complexities of these models through the construction of MATLAB code, the generation of pertinent diagrams, and extensive discussions. By doing so, We aim to enhance our understanding of neuronal processes and contribute to the larger area of computational neuroscience.

Section 1 – LIF neuron model with adaptation

The leaky integrate and fire (LIF) model is the most popular and widely used model to learn neuron's electrical properties.It is based on the standard Integrate and Fire (I&F) model but includes the leak component within the model to stimulate the adaptation of the neurons firing rate.this model divides neurons voltage changes into two part ,in the first part membrane behaves passively in the absence of the injected current or below the voltage threshold while in the second part the voltage spikes immediately when voltage reaches to the action potential threshold(due to the injected or applied current charging up the membrane).

In the first part, the voltage of the membrane potential in the absence of the injected current or voltage below its threshold,it remains linear as shown in the (Figure 1). the voltage of the membrane potential is because of the leaky capacitor or decays to a resting level (EL)

On the other hand in the second part whenever the membrane potential crosses action potential threshold value (Vth) due to the injected or applied current that charges the membrane and spikes emits immediately.after each spike model resets the membrane voltage to a value (Vreset) below the threshold(Vth) and model will continue to integrate the input from there.

1.a

The leaky integrate and fire (LIF) model is implemented as a MATLAB program named LIF1a.m.It stimulates the behavior of a neuron with spike-frequency adaptation as shown in the (Figure 1).

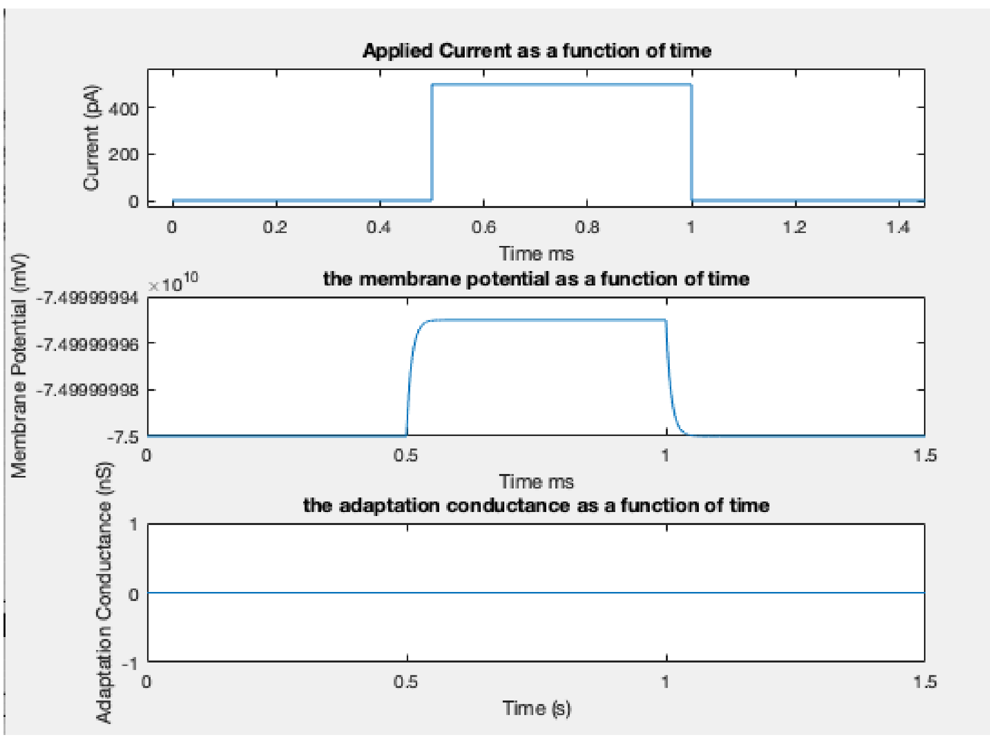

Figure 1: LIF Model with an adaptation Current

(Source: Matlab,LIF1a.m)

Due to the initial membrane potential which represents the voltage of the neurons set to the leak reversal potential (EL),initial adaptation potential set to zero and applied current(Iapp) is zero most of the time, membrane potential graph remains linear(Graph 2) up to 0.5s.when voltage of the membrane potential reaches to the voltage threshold(Vth = -50mv) due to the applied current(Iapp = 500 pA) from 0.5s to 1.5s,spikes emits immediately and it then resets to the value (Vreset) below the voltage threshold(Vth) and loops keeps generating spikes till the end of the simulation.

The adaptation conductance(GSRA),which is a dynamic conductance that influences the behavior of the neurons. As seen in the (Graph3) it remains Zero throughout the stimulation.it act as a negative feedback,as it increases to (1 ns) with each spike making it more difficult to spike again immediately after a spike.

1.b

The link between a neuron's firing rate and the applied current's amplitude is represented by the f-i curve, a frequency-current curve in the leaky integrate and fire (LIF) model.The LIF model with adaptation's f-i curve is shown as seen in Figure 2.Figure 2 illustrates how the inverse of steady state values dramatically decrease with an increase in applied current (Iapp = 500 pA), which is applied in the simulated model starting at 5 s and going through 20 levels.Interestingly, at all current levels, the steady-state interspike interval remains constant at zero, indicating that the neuron exhibits transient firing rather than settling into a sustained firing state.

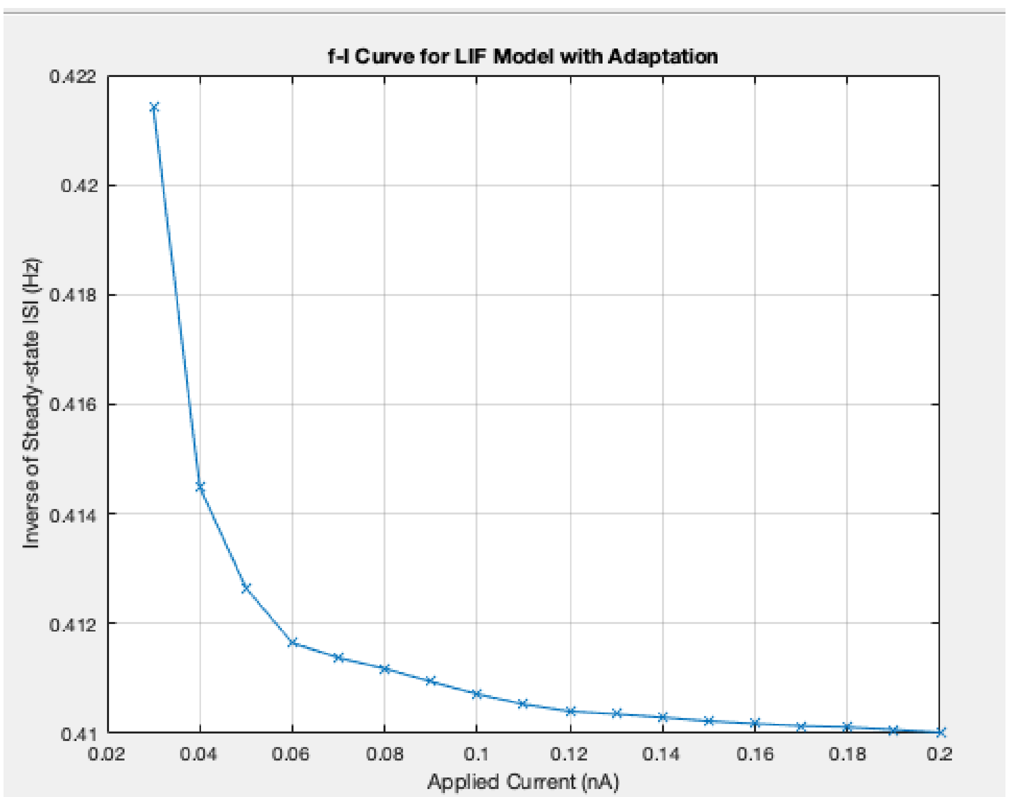

Figure 2: f-I curve for LIF Model with an adaptation Current

(Source: Matlab,LIF1b.m)

2.a

The Adaptive Exponential Integrate-and-Fire model characterizes the evolution of the membrane potential (Vm) in response to an injected current (Iapp). In Figure 3, two plots depict the applied current (Iapp) as a function of time and the membrane potential voltage (Vm) as a function of time. In the initial segment of the first graph, the applied current remains at zero until 0.5 seconds. Subsequently, between 0.5 seconds and 1 second, an applied current (Iapp = 500 pA) is evident. Similar to other Integrate-and-Fire models, when the membrane potential voltage (Vm) surpasses the voltage threshold (Vth) due to the injected current (Iapp), multiple spikes are emitted from 0.5 seconds to 1 second. Following the threshold crossing, the membrane potential voltage is reset to (Vreset), and the adaptation variable (ISRA) is increased by the spike-triggered adaptation current (b). This increase in (ISRA) leads to a reduction in the firing rate of the neuron. Towards the conclusion of the applied current pulse, around 1 second, the membrane potential gradually begins recovering to the resting state, influenced by the leaky characteristics of the neuron.

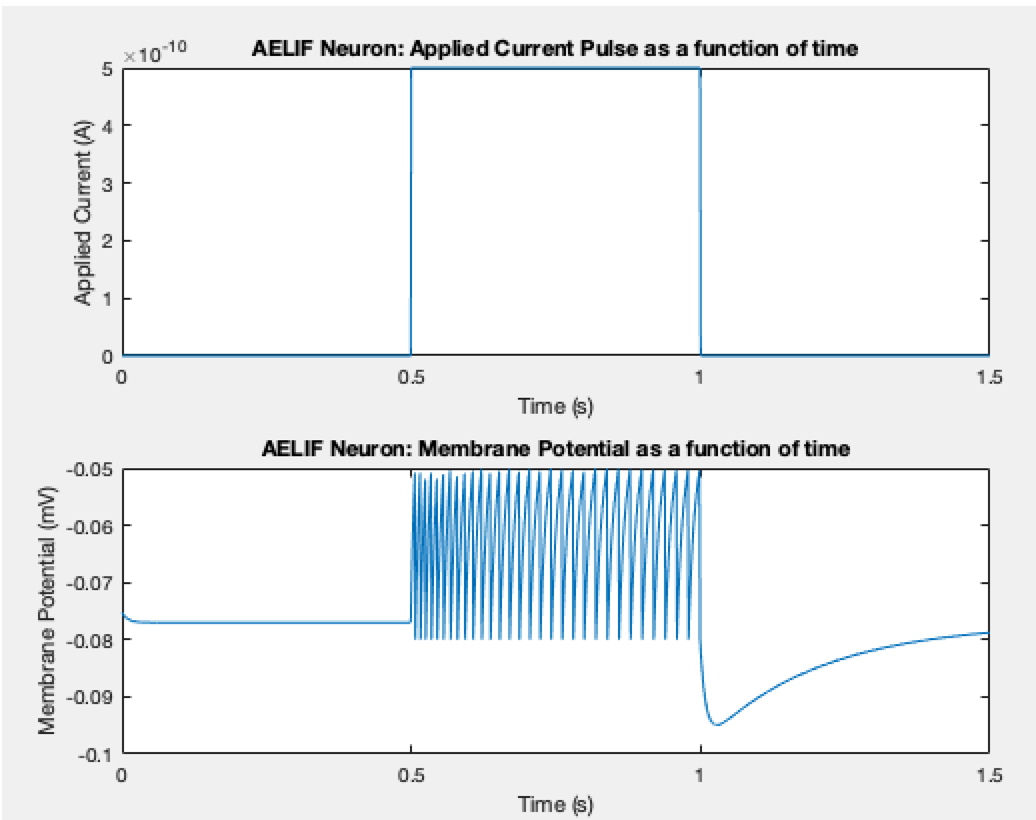

Figure 3: Adaptive Exponential Leaky Integrate-and-Fire (AELIF) Neuron Model

(Source: Matlab,AELIF1a.m)

2.b

The f-i(frequency-current) curve for the Adaptive Exponential Leaky Integrate-and-Fire (AELIF) Neuron Model can be generated by injecting the range of the applied currents into the neurons. Figure 4 depicts the graph of the f-i curve of the AELIF neuron model. The x-axis represents the amplitude of the applied current(Iapp) in pA while the y-axis represents the firing rate of the AELIF neurons in Hz. There are two separate curves plotted in the graph. The blue linear line with circle(o-) shows the inverse steady state interspike interval(inverse_steady_state_ISI). The red curve with a cross(x-) shows the initial ISI (inverse_initial_ISI) in the Matlab code (AELIF2b.m), Twenty levels of variation are made to the applied current (Iapp), which ranges from 0 to 500 pA. As the applied current increases, both steady-state ISI and Initial ISI curves show an upward trend. It appears in the graph that the steady state ISI curve reaches a point of saturation, the value after increment in the current value fails to influence the firing.

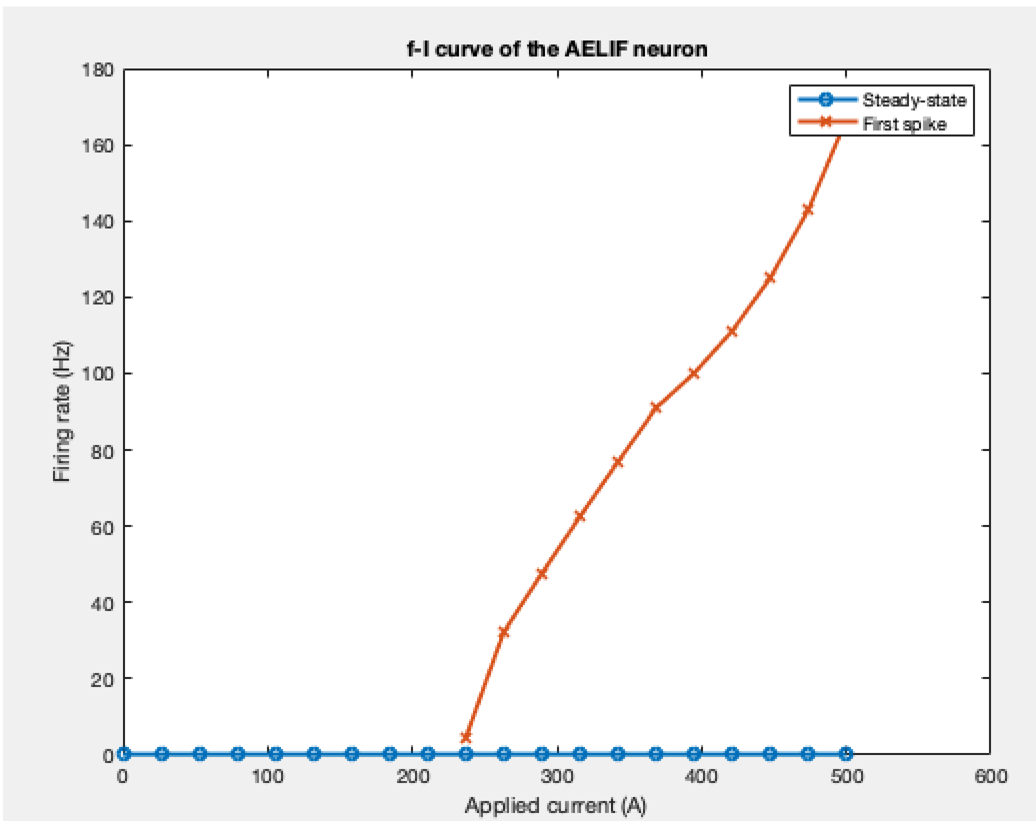

Figure 4: f-i curve of Adaptive Exponential Leaky Integrate-and-Fire (AELIF) Neuron Model

(Source: Matlab,AELIF1b.m)

Section 2 – Hodgkin-Huxley model as an oscillator

2.1

The Hodgkin-Huxley model is a mathematical model that describes the how the actual potential(nerve impulse) in neurons are generated.This model explains the relationship between the four gating variables sodium activation, *m*, sodium inactivation, *h*, potassium activation, *n*, membrane potential, *V and the injected current I as seen in the Figure 5.*

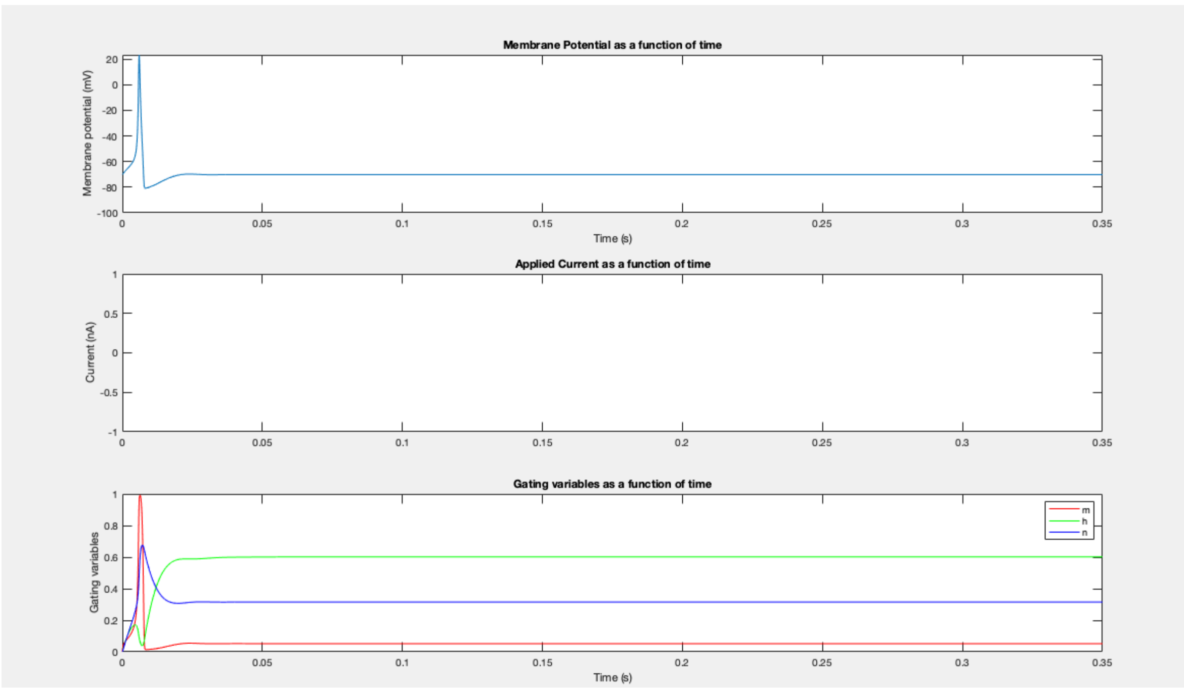

Figure 5:**The Hodgkin-Huxley model**

(Source: Matlab,HHmodel.m)

In the First graph,At the resting state most of the voltage gated sodium channels and Voltage gated potassium channels are closed.when the voltage of the membrane potential due to the leakage of the small movements of sodium and potassium or the being charged by the injected current ,crosses the threshold nearly -55 mV,it triggers the action potential and it starts opening the voltage gated sodium channels so that sodium ios(Na+) rush into the neurons,causing a rapid and large depolarization and this phase known as the rising phase of the action potential.and at the repolarization phase voltage gated potassium channel opens ,allows the potassium ions to exit the cell.due to efflux of positive potassium ions restores the negative charge inside the cell leading to repolarization. repolarization often overshoots the resting potential,causing a brief hyperpolarization due to delayed closure of the voltage gated potassium channels.at the last after an action potential the neurons enters into the refractory period which prevents the backward actual potential propagation and ensure the one way transmission of the signals.

2.2

Figure 6 illustrates the correlation between membrane potential and applied currents. In the initial graph, the applied current undergoes a step increase to 0.22 nA over 100 ms, commencing from 0.1 ms and concluding at 0.2 ms. The second graph depicts the membrane potential as a function of time, revealing small oscillations post-return to the resting state. This phenomenon is recognized as subthreshold oscillations or neuronal refractoriness.Notably,In the second graph when applied currents are applied, minor fluctuations are observed that fail to surpass the threshold for action potential generation.This situation can arise if the injected current lacks the strength to elevate the membrane potential to levels requisite for activating voltage-gated sodium channels, pivotal for the swift depolarization phase inducing action potential spikes.Within the depicted scenario, an injected current of 0.22 nA for 100 ms proves insufficient to propel the membrane potential to the threshold, thereby precluding action potential generation and manifesting only subtle spikes.

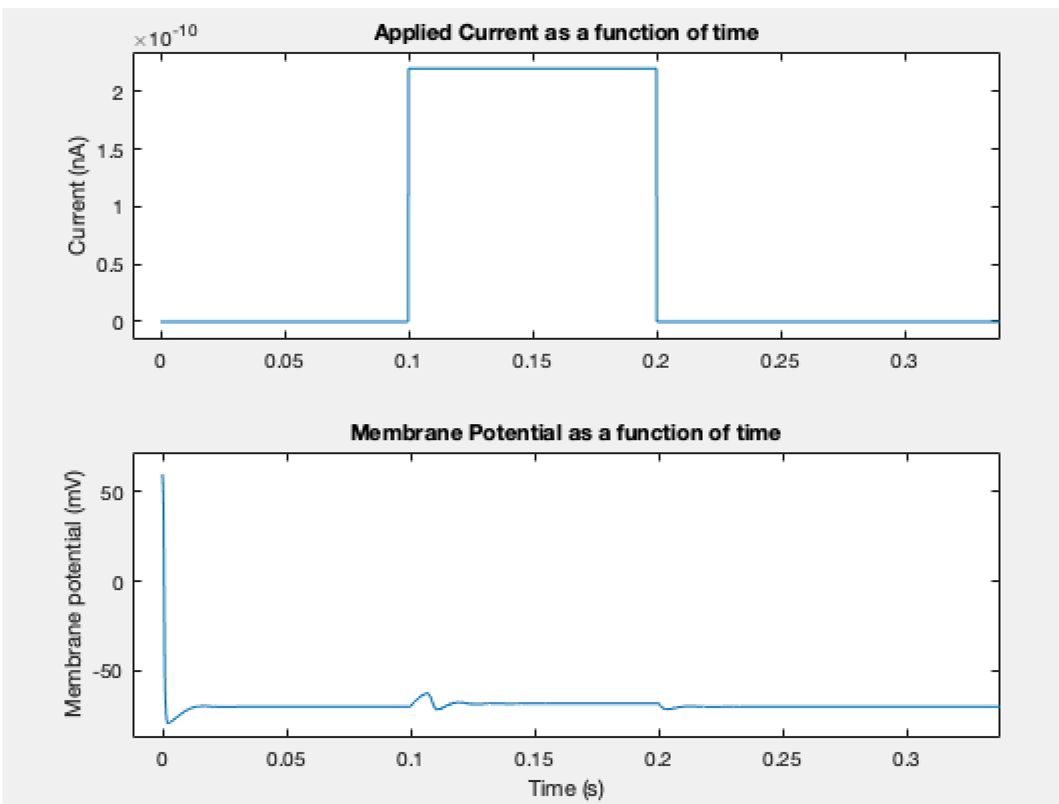

Figure 6:**The Hodgkin-Huxley model**

(Source: Matlab,HHmodel22.m)

2.3

In the simulated Figure.7,the dynamics of membrane potential in response to applied current steps is plotted as a graph.in this external current applied as a step function with a delay of 10 milliseconds and a pulse duration of 5 milliseconds in between 0.1sec to 0.2sec.From the first graph it is clearly visible that the due to the hyperpolarizing spike after potential the voltage is lower. More power is needed to reach the firing threshold or it can be due to a large portion of channels opening immediately after a spike,the resistance of the membrane is reduced.so the depolarizing effect of a stimulating current pulse decays therefore faster immediately after the spike than 0.1ms later.so a long delay or high amplitude is needed to spikes generated due to the resting state of the neurons.

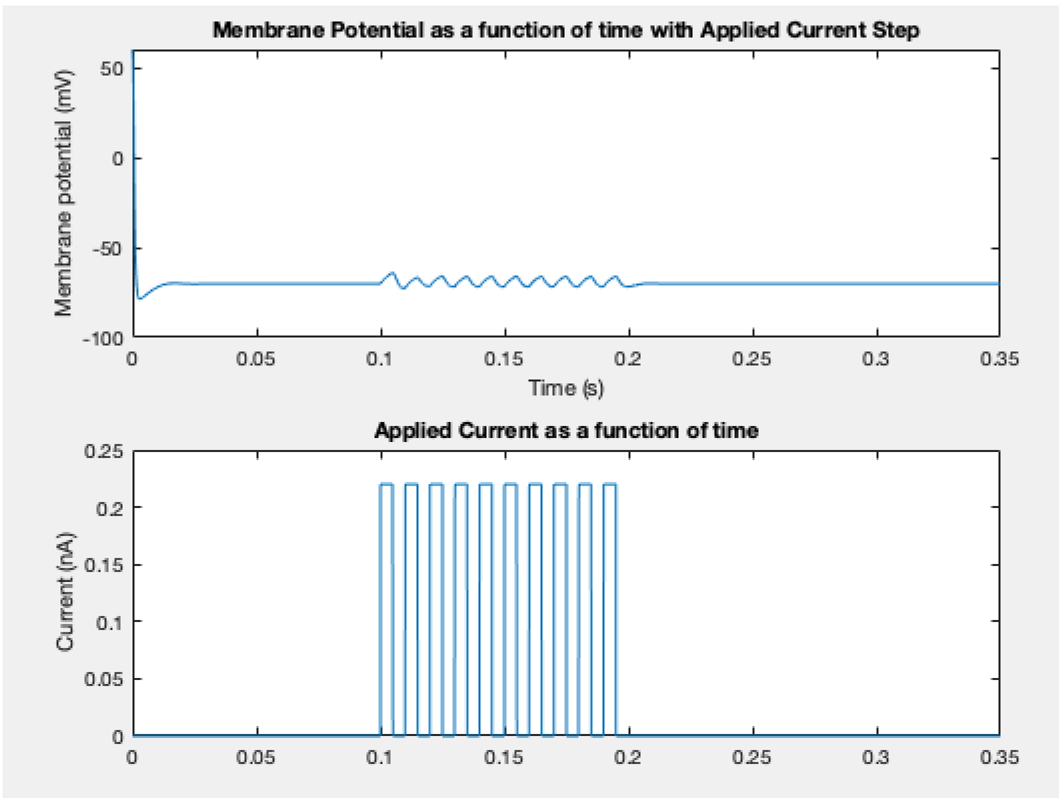

Figure 7:**The Hodgkin-Huxley model**

(Source: Matlab,HHmodel23.m)

2.4

The graph illustrates how inhibitory pulses affect the membrane potential of a neuron.In the first subplot black bars represents a inhibitory pulses which are applied periodically with a regular interval of 20ms for a duration of 5 ms.the blue line graph shows the membrane potential as a function of time.with increase of inhibitory,the voltage of the membrane potential declines,reflecting inhibitory synaptic input.i.e the amplitude of the inhibitory pulse at a initial stage is low that affects the low on membrane potential.and keeps going its affection keeps increases and the voltage of the membrane potential keeps declining.

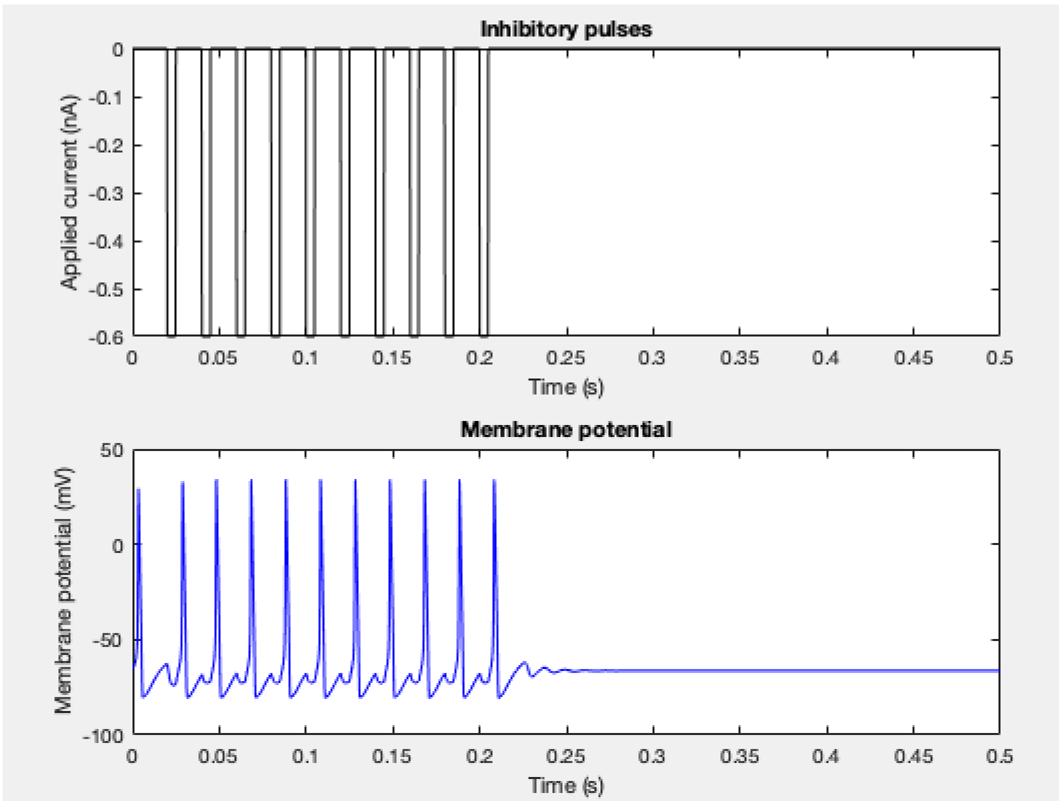

Figure 8:**The Hodgkin-Huxley model**

(Source: Matlab,HHmodel24.m)

2.5

The chart depicts the correlation between the excitatory pulse and the membrane potential voltage. The excitatory pulse, in contrast to inhibitory pulses, results in an elevation of the membrane potential, ultimately triggering an action potential. In Figure 9, the initial graph illustrates a transient increase in the excitatory pulse, rising from 1 nA to a 5 ms pulse duration at the 100 ms time point. The second graph demonstrates the membrane potential response corresponding to the excitatory pulse. As the amplitude of the excitatory pulse grows, the voltage across the membrane increases, leading to membrane depolarization.

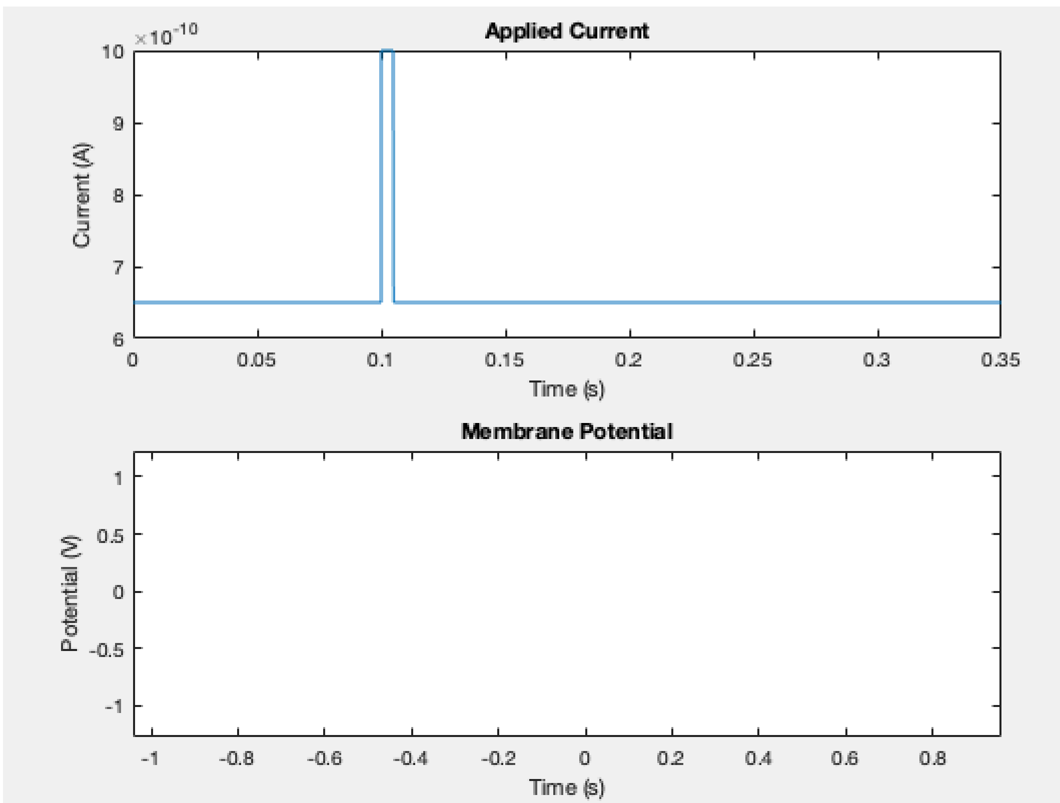

Figure 9:**The Hodgkin-Huxley model**

(Source: Matlab,HHmodel25.m)

2.6

The given graph models the impact of introducing an excitatory pulse with increased baseline current, illustrating how such a pulse could influence the membrane potential of a neuron.In Figure 10, the initial graph illustrates a increase in the excitatory pulse, rising from 1 nA to a 5 ms pulse duration at the 100 ms time point with higher baseline current of 0.7ms.

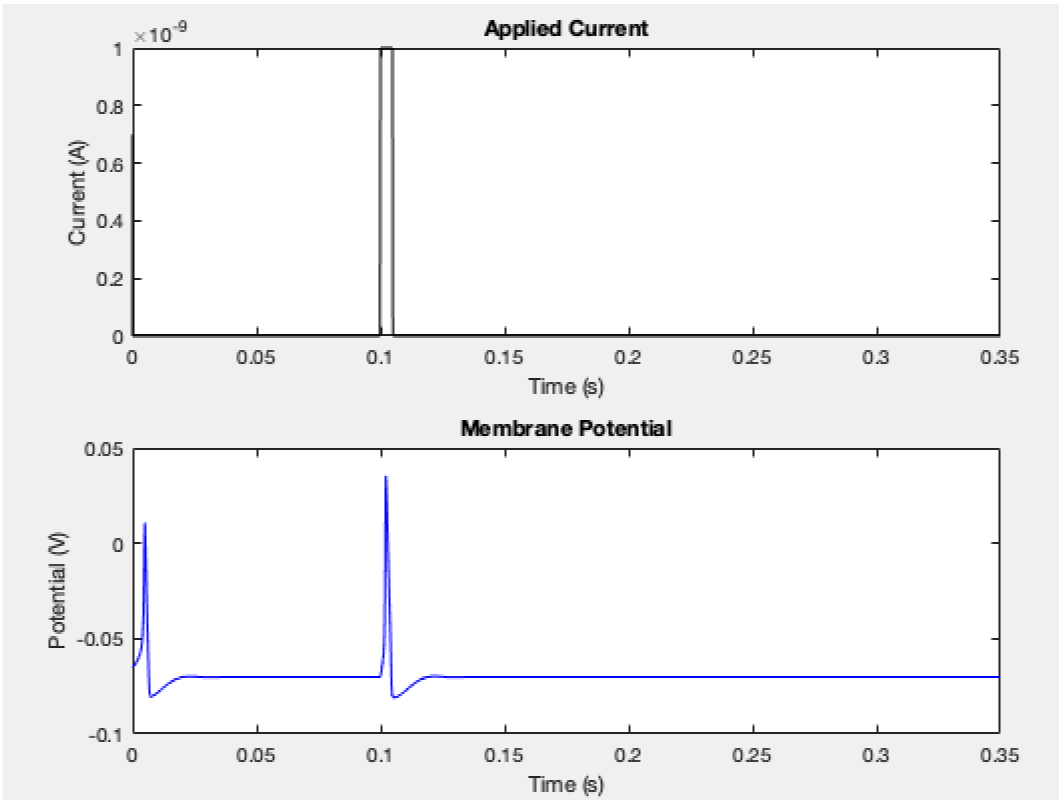

Figure 10:**The Hodgkin-Huxley model**

(Source: Matlab,HHmodel26.m)

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