EE-746 Neuromorphic Engineering
Assignment 3

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1. Representing Synaptic Connectivity and Axonal Delays

A : Creating cell arrays to store connectivity information

```
%% Specifying the network
%a->1 b->2 c->3 d->4 e->5

for i = 1:N
        fanout{i} = [];
        weight{i} = [];
        delay{i} = [];
end

fanout{2} = [1,5];
weight{2} = [3000,3000];
delay{2} = [1e-3,8e-3];

fanout{3} = [1,5];
weight{3} = [3000,3000];
delay{3} = [5e-3,5e-3];

fanout{4} = [1,5];
weight{4} = [3000,3000];
delay{4} = [9e-3,1e-3];
```

B : Synaptic current and response of neurons

Case - I

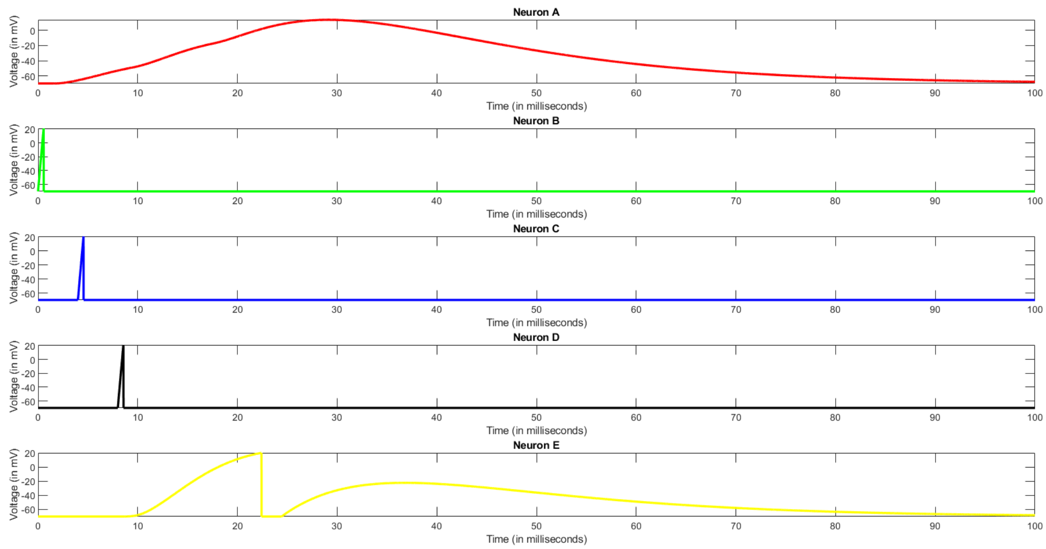

Figure 1: Membrane Potential vs. Time

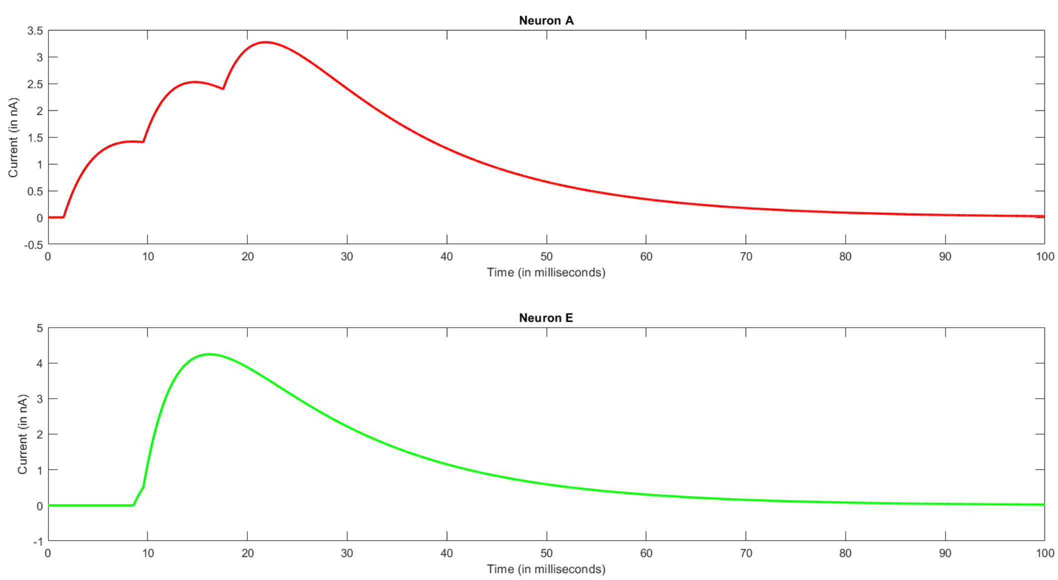

Figure 2: Synaptic Current vs. Time. Neurons B, C and D would have zero synaptic current as they do not have any pre-neurons

Case - II

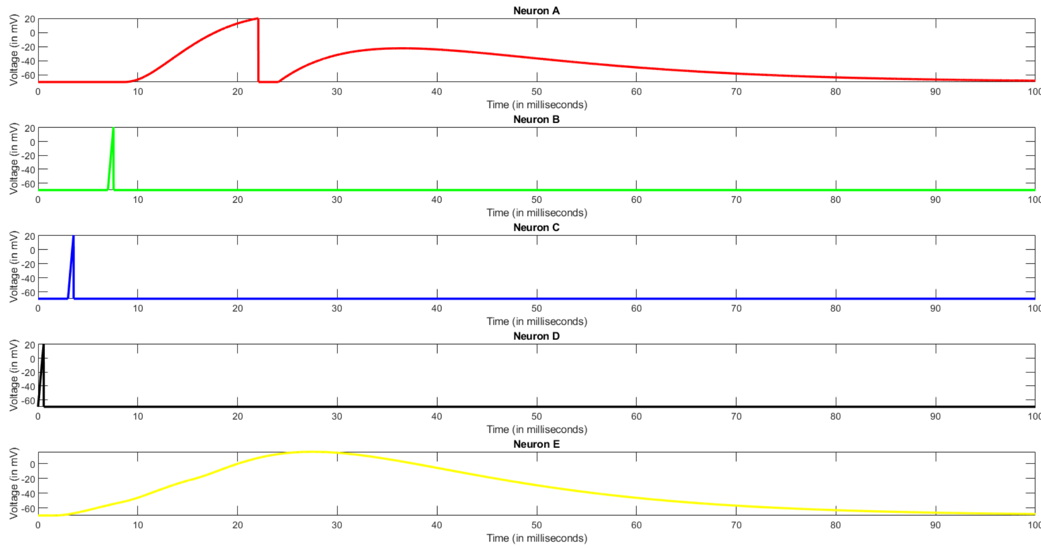

Figure 3: Membrane Potential vs. Time

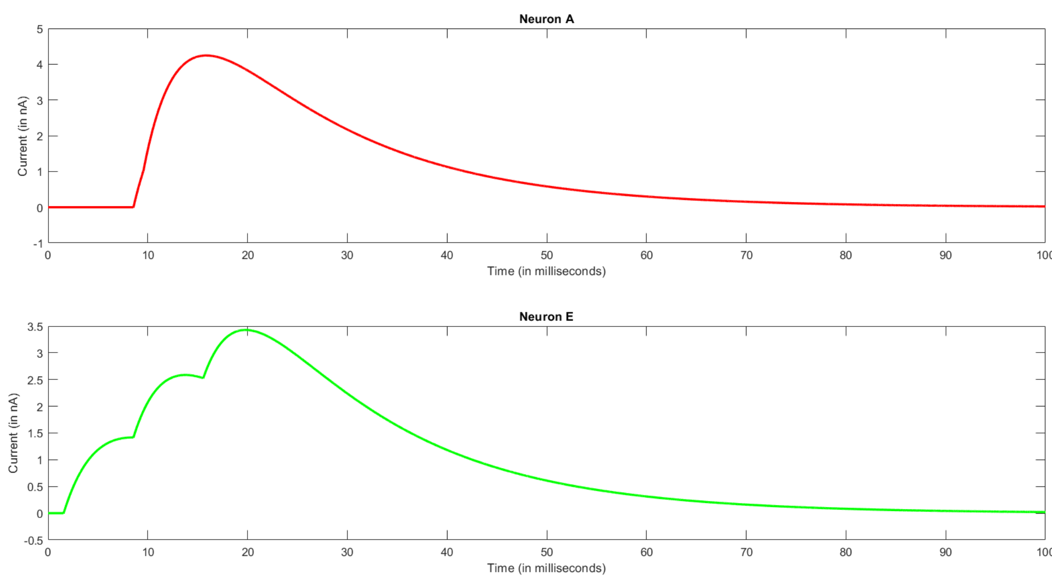

Figure 4: Synaptic Current vs. Time. Neurons B, C and D would have zero synaptic current as they do not have any pre-neurons

2. Dynamical Random Network

A : Raster plot for $N = 500$ spikes

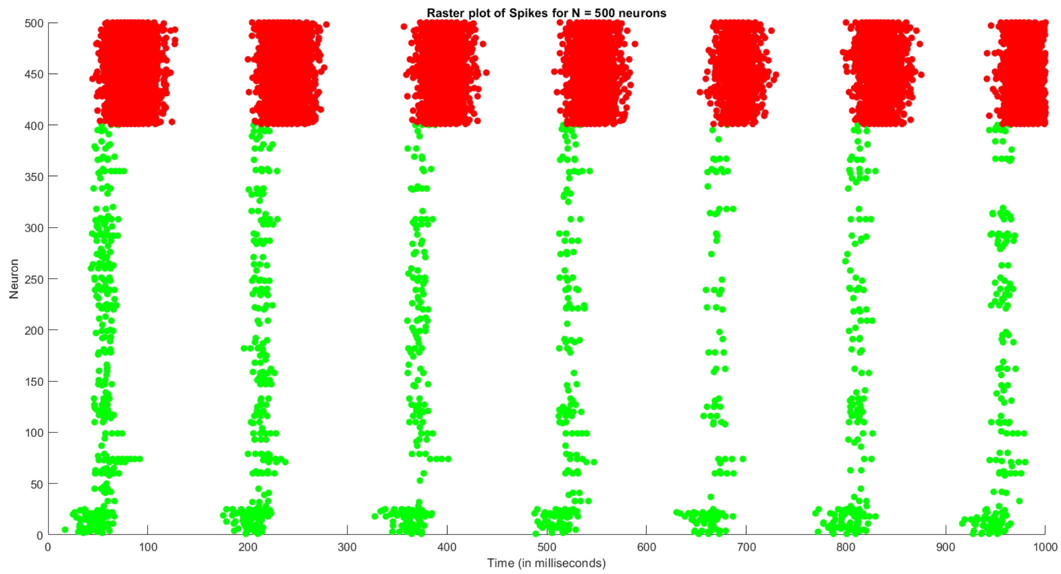

Figure 5: Raster plot of spikes for 500 Neurons. GREEN = Excitatory RED = Inhibitory

B : $R_e(t)$ and $R_i(t)$ vs time

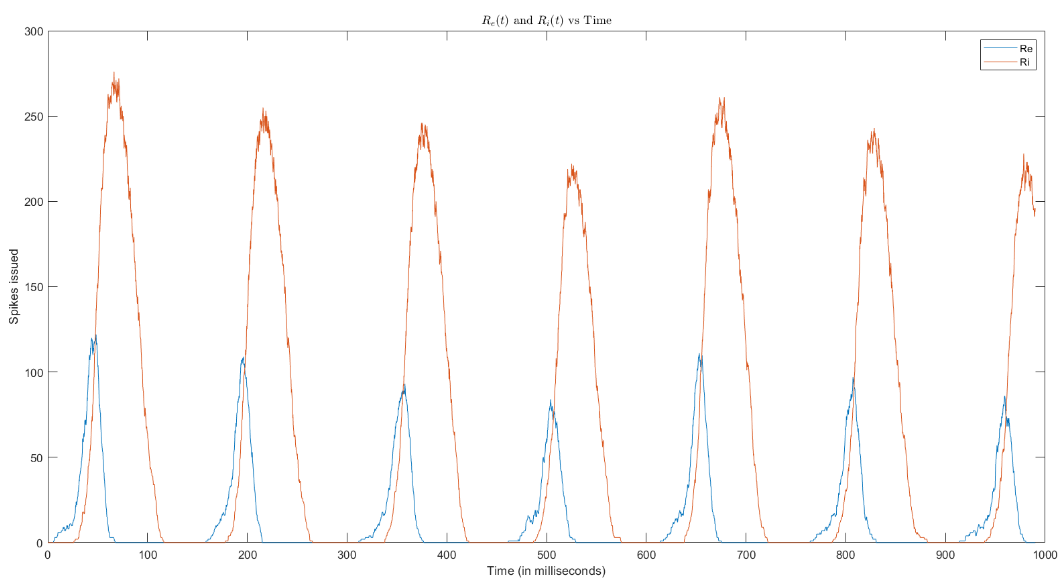

Figure 6: $R_e(t)$ and $R_i(t)$ vs time

C : Mechanism underlying the behavior

The Poisson stimulus applied to the excitatory neurons causes them to spike. This develops synaptic current in the neurons connected to the initial neurons, causing them to spike as well and so on.
When the inhibitory neurons start to spike, they decrease the synaptic currents to the excitatory neurons (as the weights of the inhibitory neuron's connections to excitatory neurons are negative). The number of inhibitory spikes issued vastly outnumbers the excitatory spikes issued as can be seen in Figure 6, causing the excitatory spiking to decrease to almost nil, which causes the inhibitory spiking to decrease as well (since all inputs to inhibitory neurons are excitatory neurons), hence causing the system to go back to its original state, where the cycle keeps on continuing.

3. Dynamics of Smaller Networks

A : Raster plot for $N = 200$ spikes

The network continues to spike incessantly, as the excitation is high/inhibition is low, as can be observed in Figure 8, for the spiking to go down.

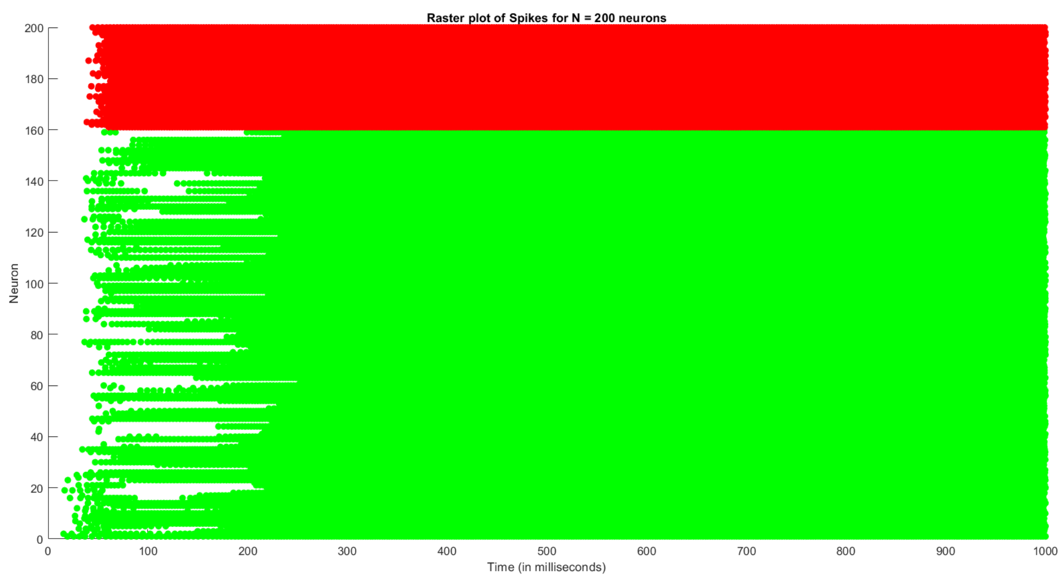

Figure 7: Raster plot of spikes for 200 Neurons. GREEN = Excitatory RED = Inhibitory

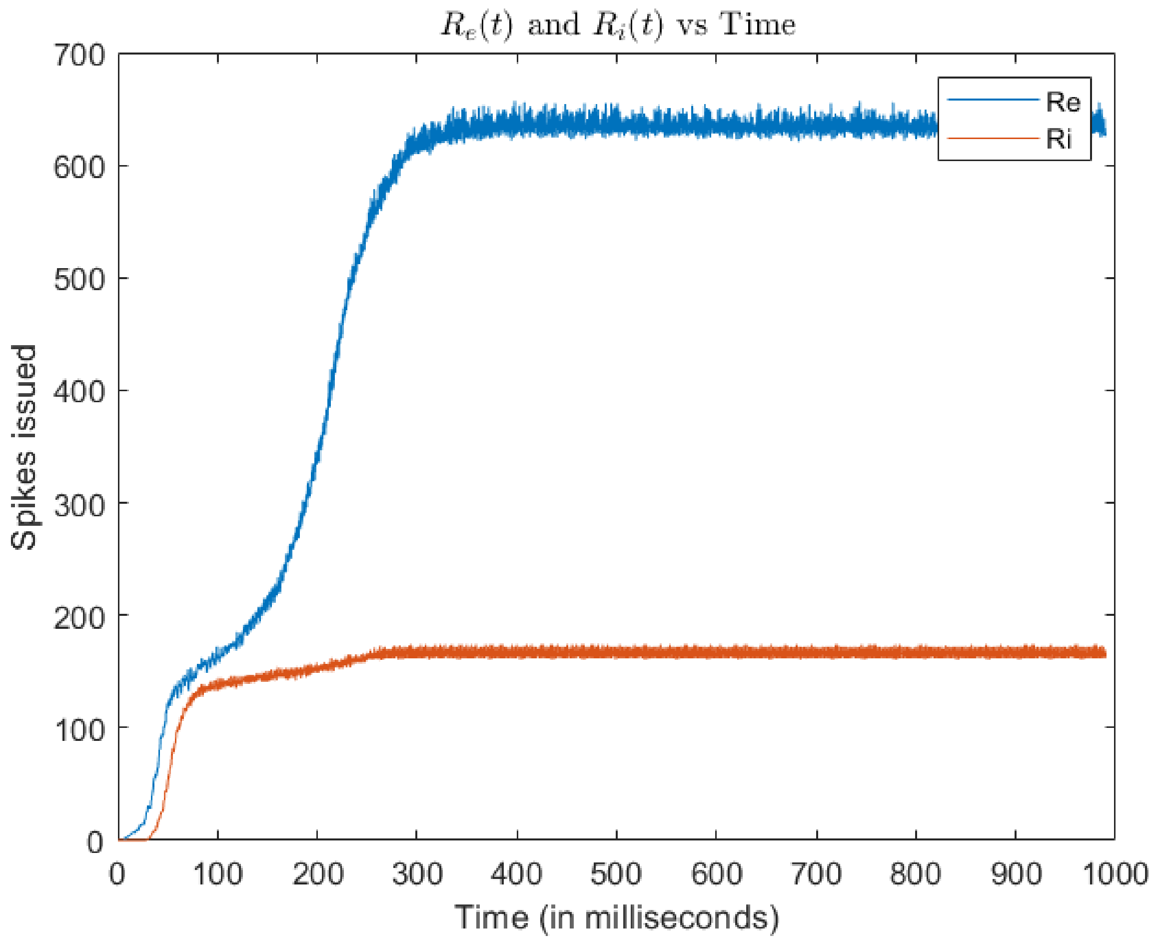

Figure 8: $R_e(t)$ and $R_i(t)$ vs time for $w_e = -w_i = 3000$

B : Behavior of network for other values of synaptic strength

1. $w_e = -w_i =$ 4000

Increasing the synaptic weight makes the network spike continuously, as the excitation remains high and inhibition remains low, as can be observed in Figure 10.

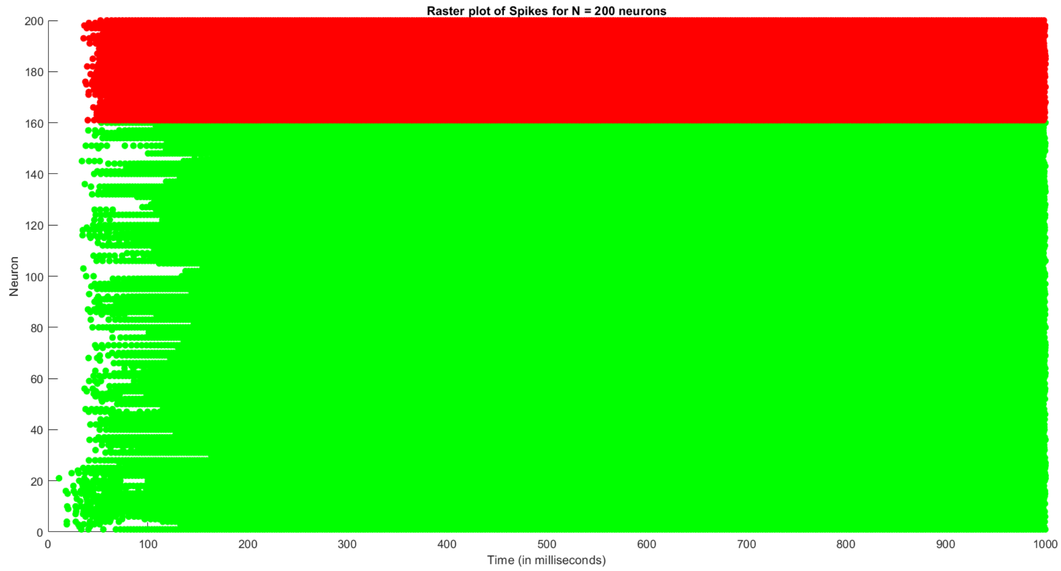

Figure 9: Raster plot of spikes for 200 Neurons. GREEN = Excitatory RED = Inhibitory

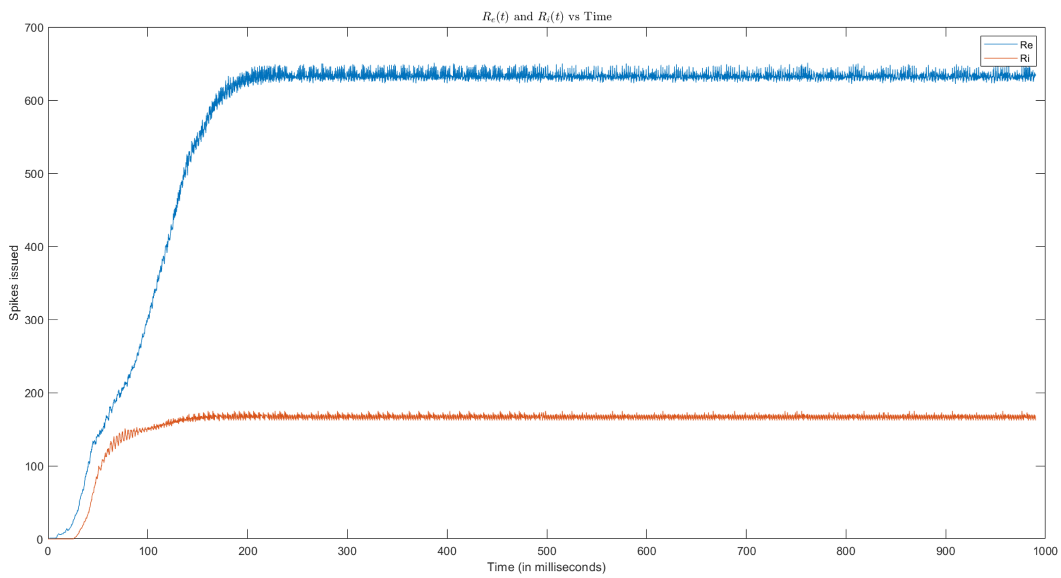

Figure 10: $R_e(t)$ and $R_i(t)$ vs time for $w_e = -w_i = 4000$

2. $w_e = -w_i =$ 2000

Decreasing the synaptic weight causes less excitation and gives the inhibition a chance to dominate, causing spiking behavior to occur in the network.

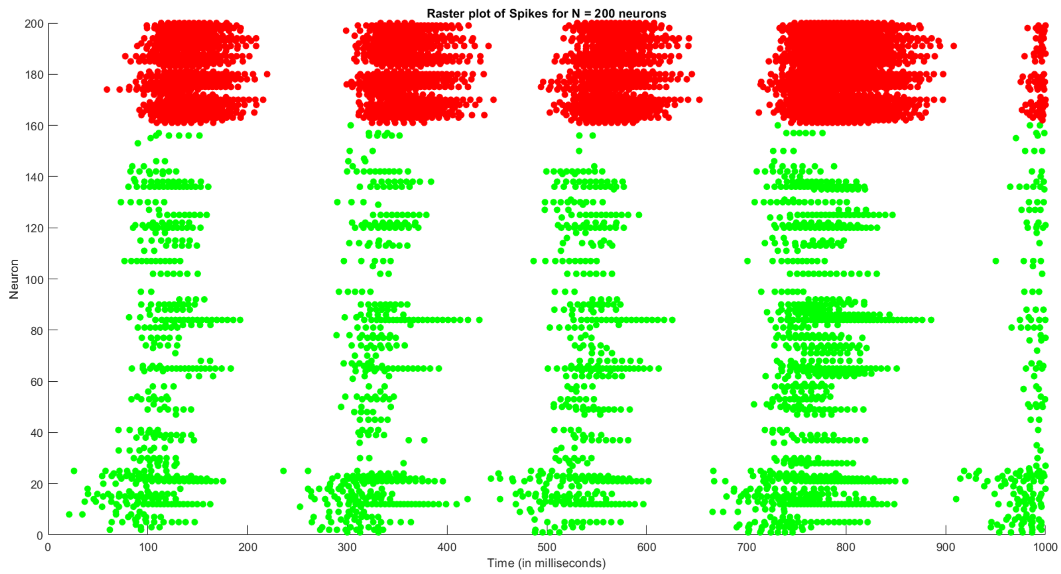

Figure 11: Raster plot of spikes for 200 Neurons. GREEN = Excitatory RED = Inhibitory

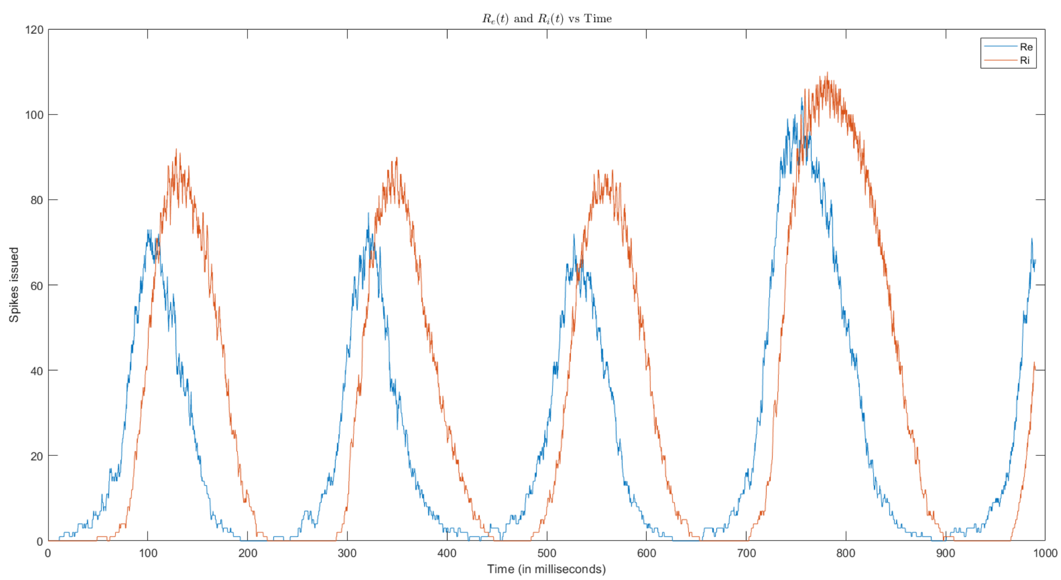

Figure 12: $R_e(t)$ and $R_i(t)$ vs time for $w_e = -w_i = 2000$

3. $w_e = -w_i =$ **1500**

Decreasing the weights even further causes more time to be taken for the neurons to fire as the synaptic current takes time to build up. This causes the network to have less spikes in the specified time-frame.

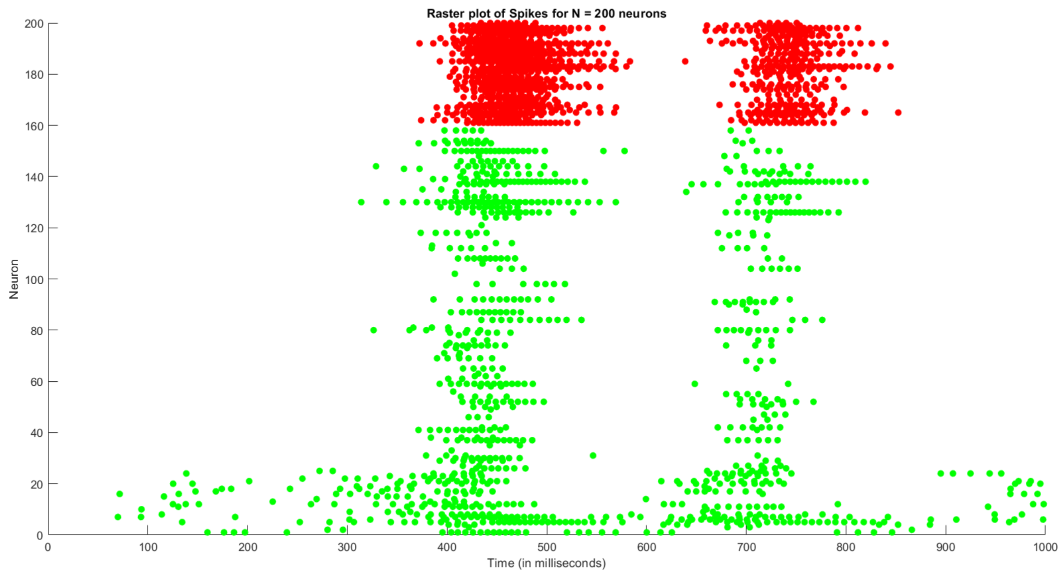

Figure 13: Raster plot of spikes for 200 Neurons. GREEN = Excitatory RED = Inhibitory

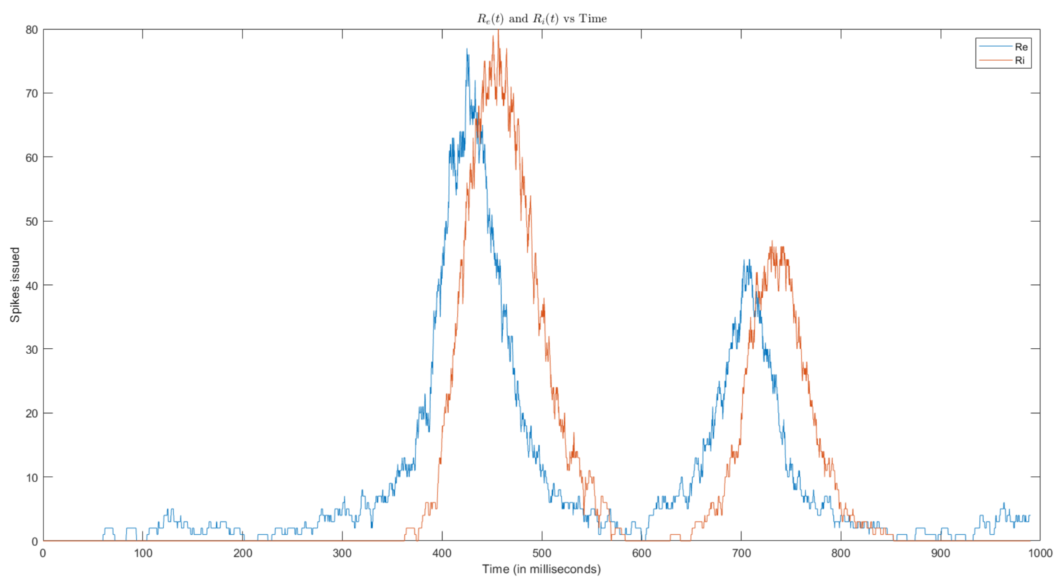

Figure 14: $R_e(t)$ and $R_i(t)$ vs time for $w_e = -w_i = 1500$

C

For smaller networks, $|w_e| = |w_i|$ is unable to give the required spiking behavior. This occurs as inhibitory spikes are unable to dominate the excitatory spikes issued. For obtaining the spiking behavior, *inhibition* should be *increased* in the network so that it is able to return back to a default state from where the spiking can begin again.

D : Modification of the synaptic configuration $(w_e = -\gamma w_i)$

1. $\gamma = 0.5$

$\gamma = 0.5$ implies that inhibition has been suppressed, which causes all neurons to fire continuously. As can be seen from Figure 16, excitatory spikes dominates inhibitory spiking.

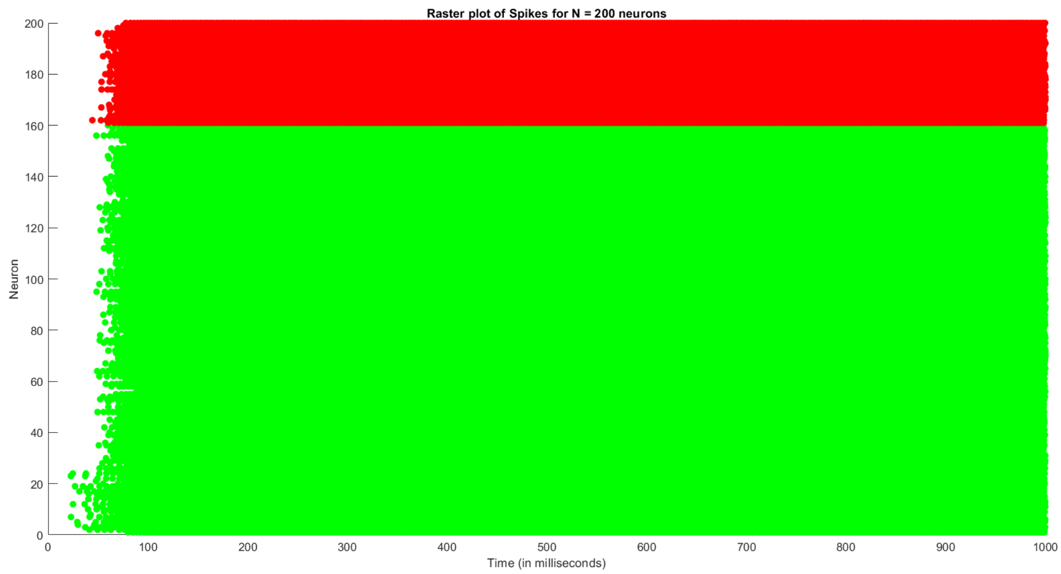

Figure 15: Raster plot of spikes for 200 Neurons. GREEN = Excitatory RED = Inhibitory

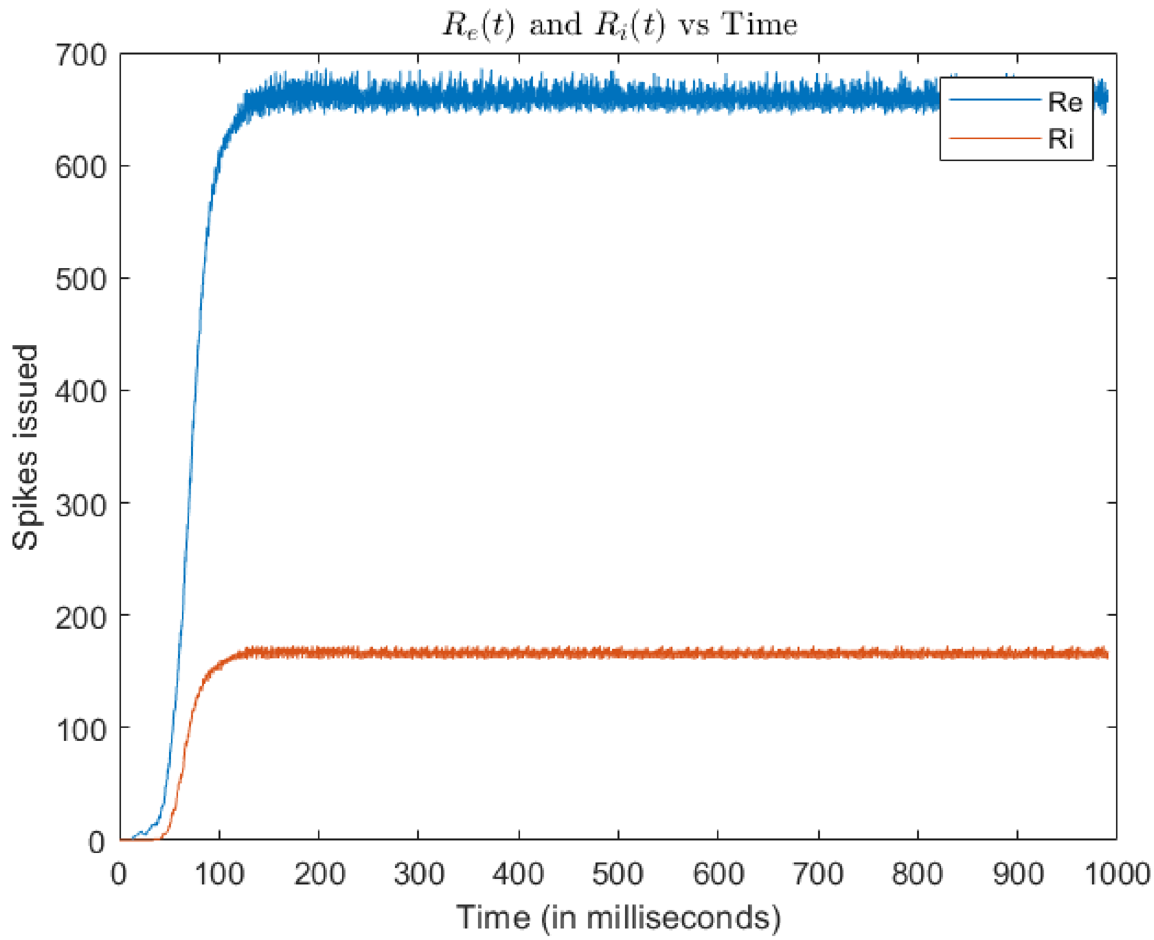

Figure 16: $R_e(t)$ and $R_i(t)$ vs time for $\gamma = 0.5$

2. $\gamma = 1.5$

As the magnitude of inhibitory weights starts to increase with respect to excitatory weights, we begin to observe spiking behavior in the network. However, inhibition is still not strong enough to take the network to near its resting state.

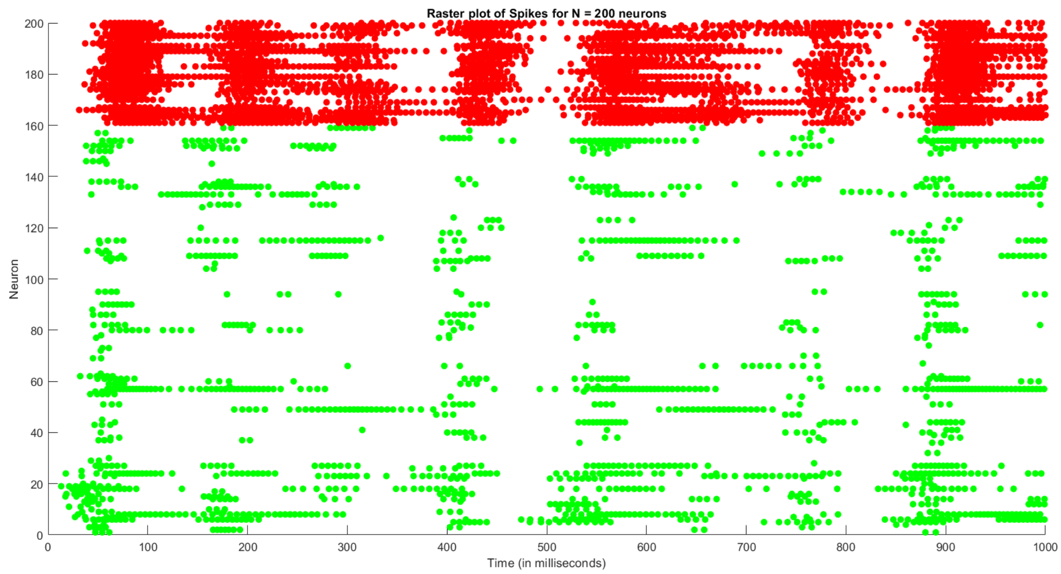

Figure 17: Raster plot of spikes for 200 Neurons. GREEN = Excitatory RED = Inhibitory

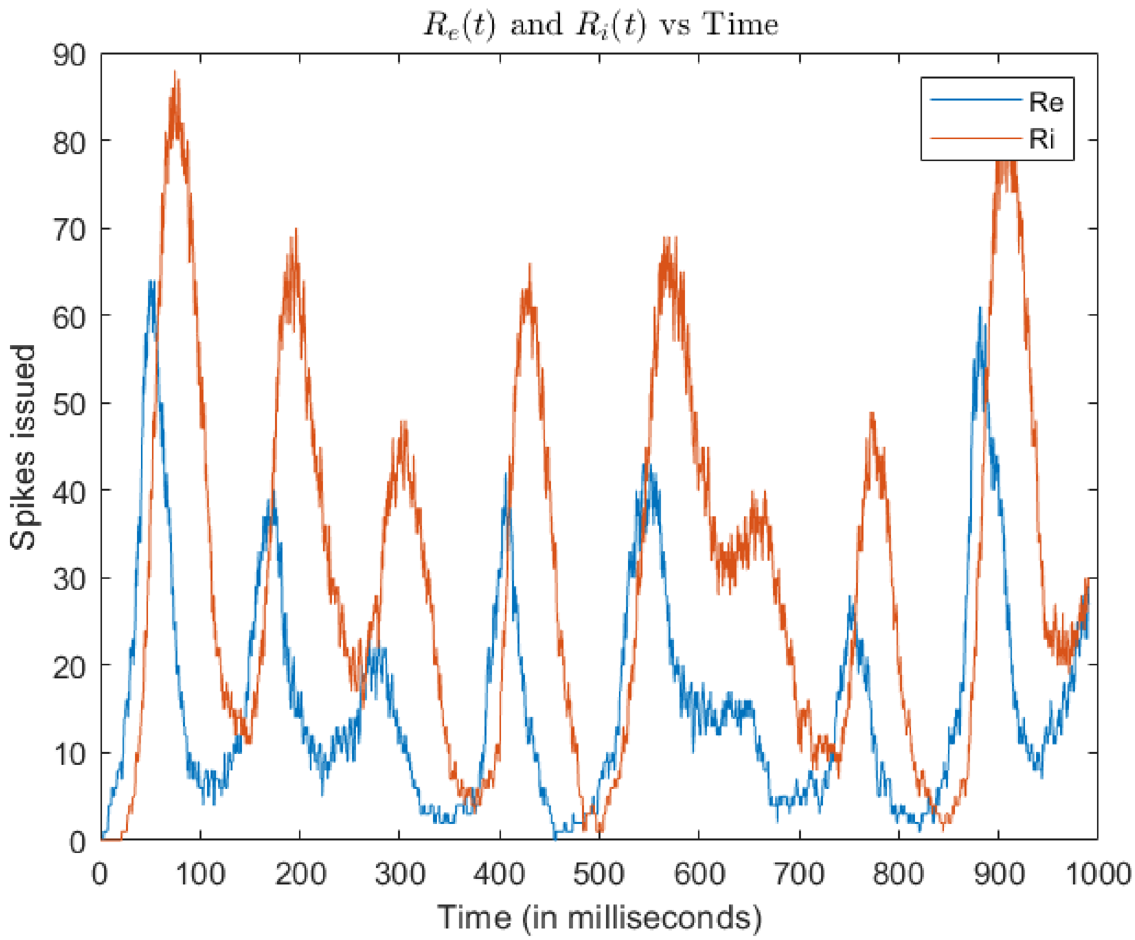

Figure 18: $R_e(t)$ and $R_i(t)$ vs time for $\gamma = 1.5$

3. $\gamma = 2$

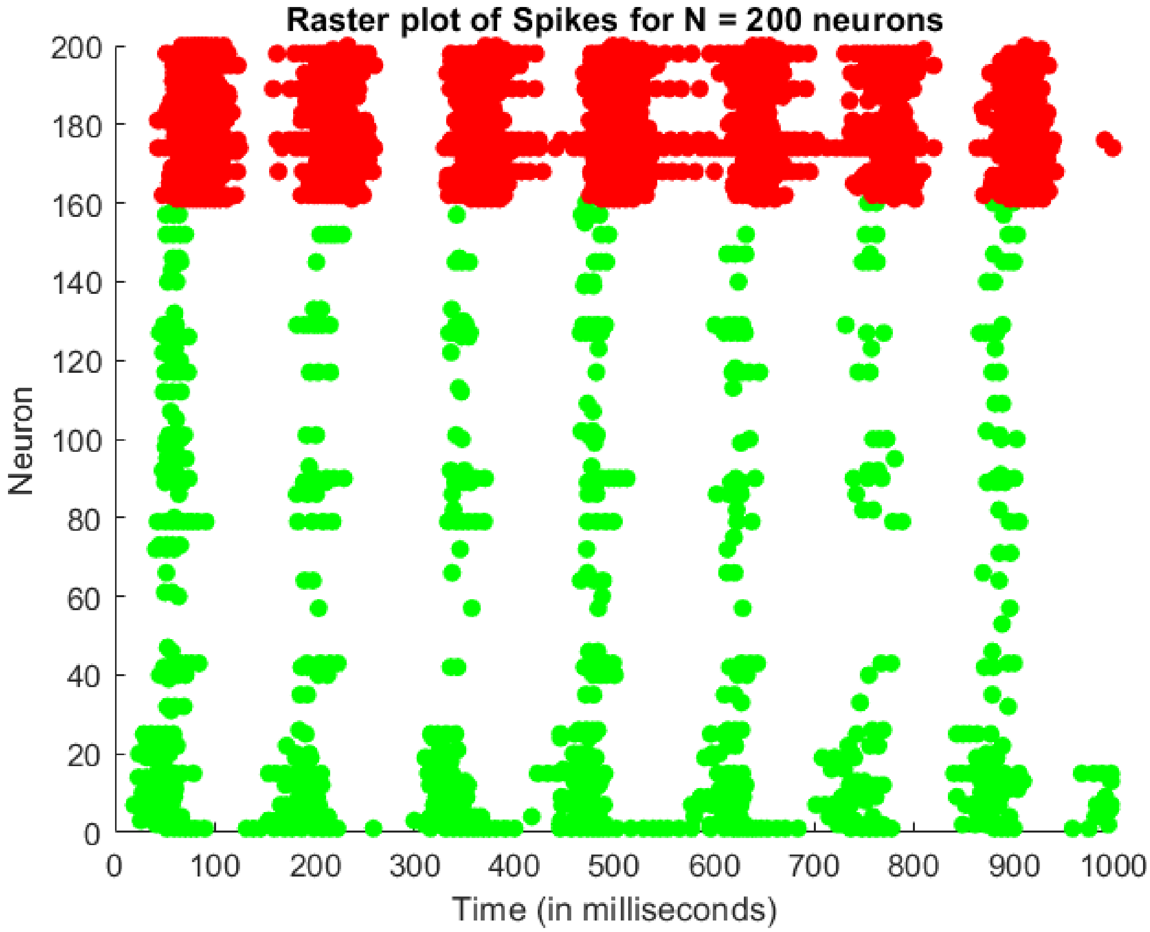

Figure 19: Raster plot of spikes for 200 Neurons. GREEN = Excitatory RED = Inhibitory

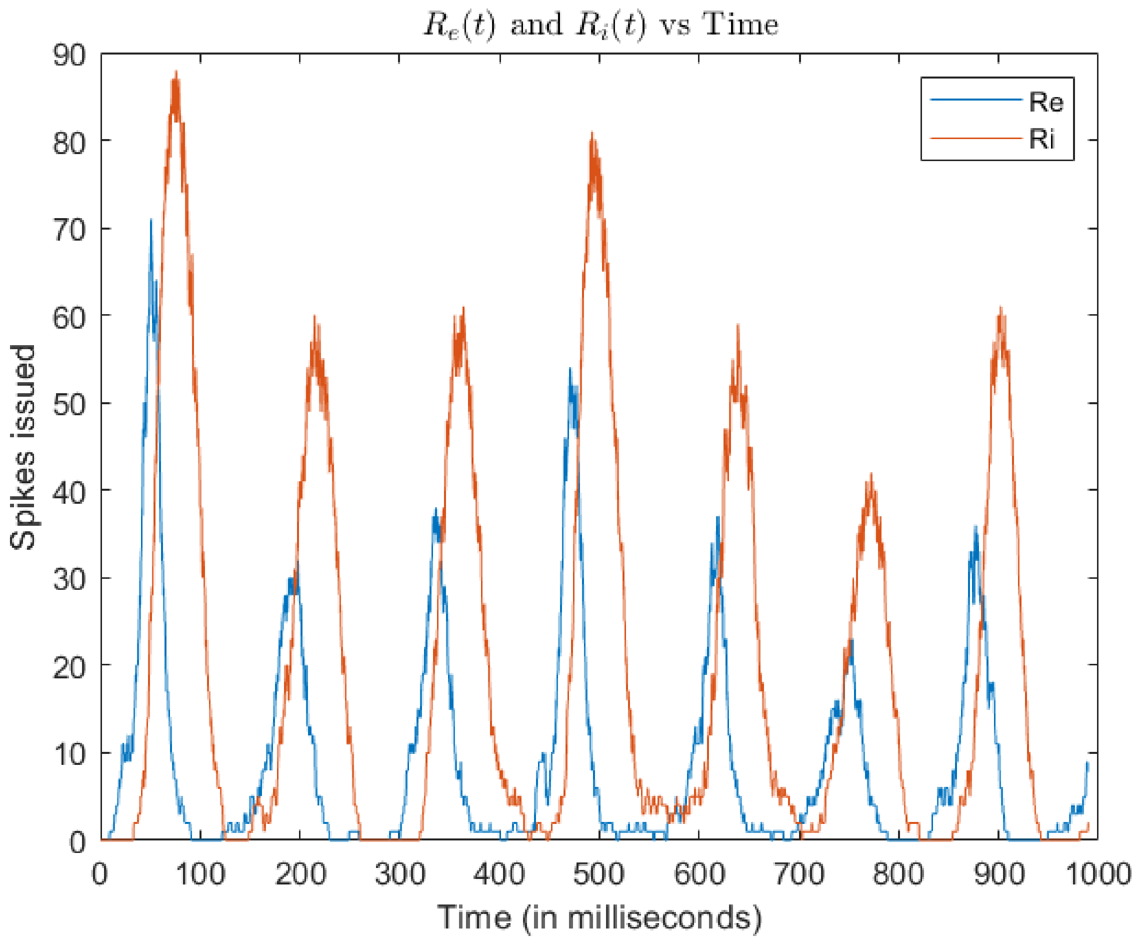

Figure 20: $R_e(t)$ and $R_i(t)$ vs time for $\gamma = 2$

4. $\gamma = 2.5$

We start to observe expected spiking behavior of the network, when inhibition is just high enough to take the system to near its resting state.

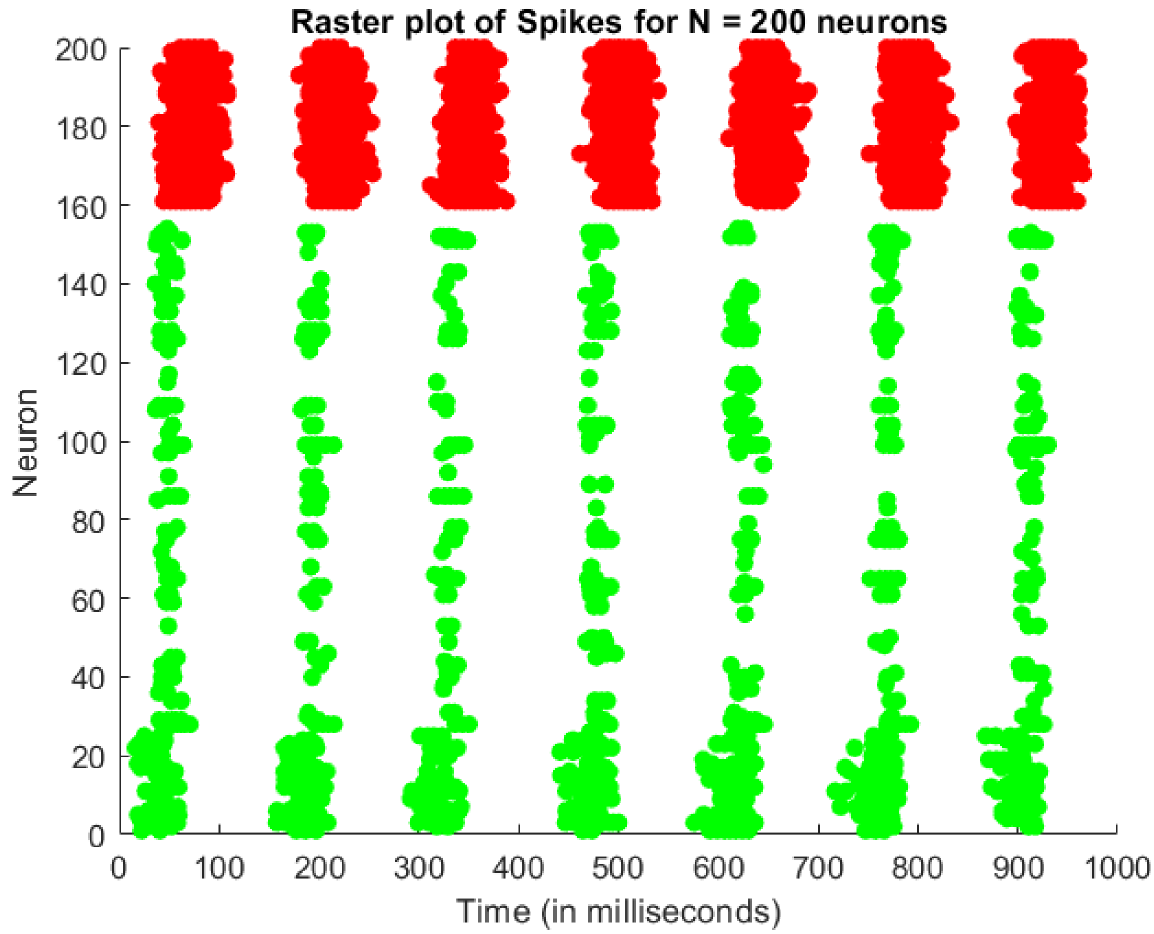

Figure 21: Raster plot of spikes for 200 Neurons. GREEN = Excitatory RED = Inhibitory

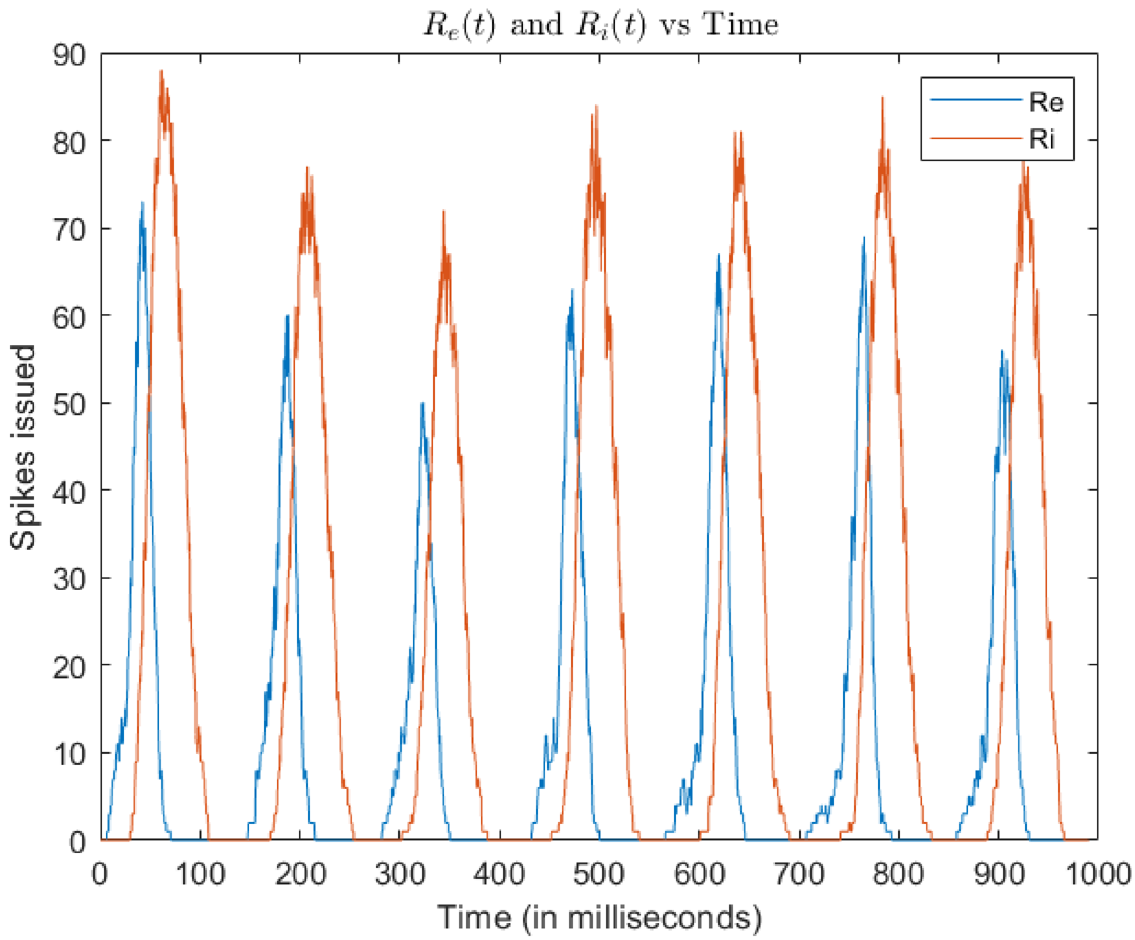

Figure 22: $R_e(t)$ and $R_i(t)$ vs time for $\gamma = 2.5$

4. Adjusting the Weights Dynamically

A : Snippet of code implementing Timing Dependent Plasticity

```
%----------------------STDP---------------
%---Upstream
for i = 1:length(Upstream{j})
    %find most recent spike
    pre_neuron = Upstream{j}(i);%index of the pre_neuron
    index = Fanout{pre_neuron} == j; %index of current neuron
    dly = Delay{pre_neuron}(index);
    for m = length(spike_time{pre_neuron}):-1:1  %start loop from the last element
        if(spike_time{pre_neuron}(m)+dly<t(k))
            Weight{pre_neuron}(index) = Weight{pre_neuron}(index) +
            Weight{pre_neuron}(index)*Aup*
            exp(-(t(k)-(spike_time{pre_neuron}(m)+dly))/tau_l);
            break;
        end
```

```
    end
end
%-----------
%-Downstream
for i = 1:length(Fanout{j})
    post_neuron = Fanout{j}(i);%index of the post_neuron
    dly = Delay{j}(i);
    if(~isempty(spike_time{post_neuron}))
        Weight{j}(i) = Weight{j}(i) +
        Weight{j}(i)*Adown*
        exp(-(t(k)-(t(k)+dly-spike_time{post_neuron}(end)))/tau_l);
    end
 end
%-----------
%-----------------------------------------
```

B : Average excitatory synaptic strength vs. time

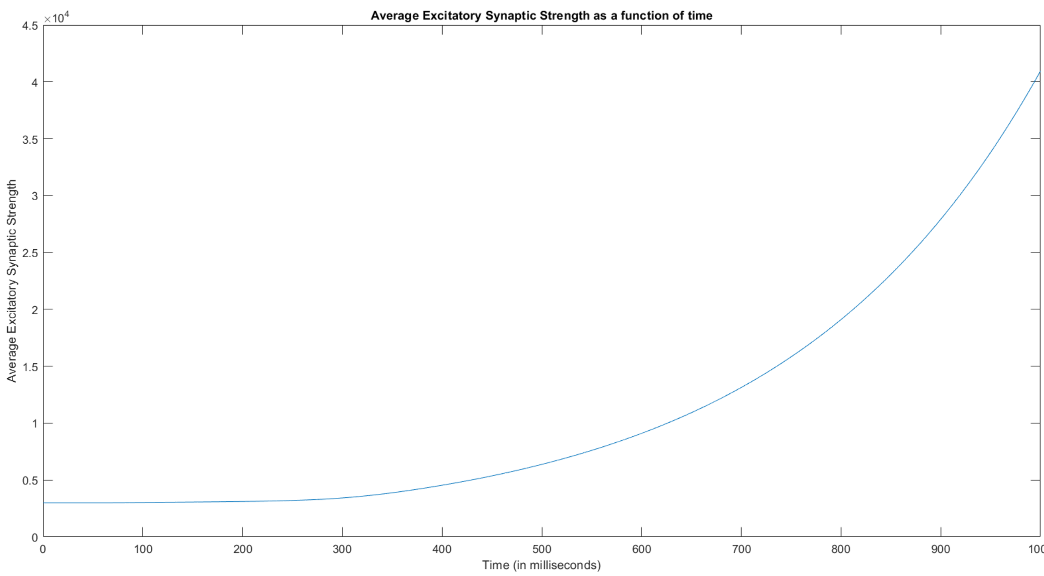

Figure 23: Average Excitatory Synaptic Strength vs. Time. Assuming STDP (A_{up} = 0.01 and A_{down} = -0.02)

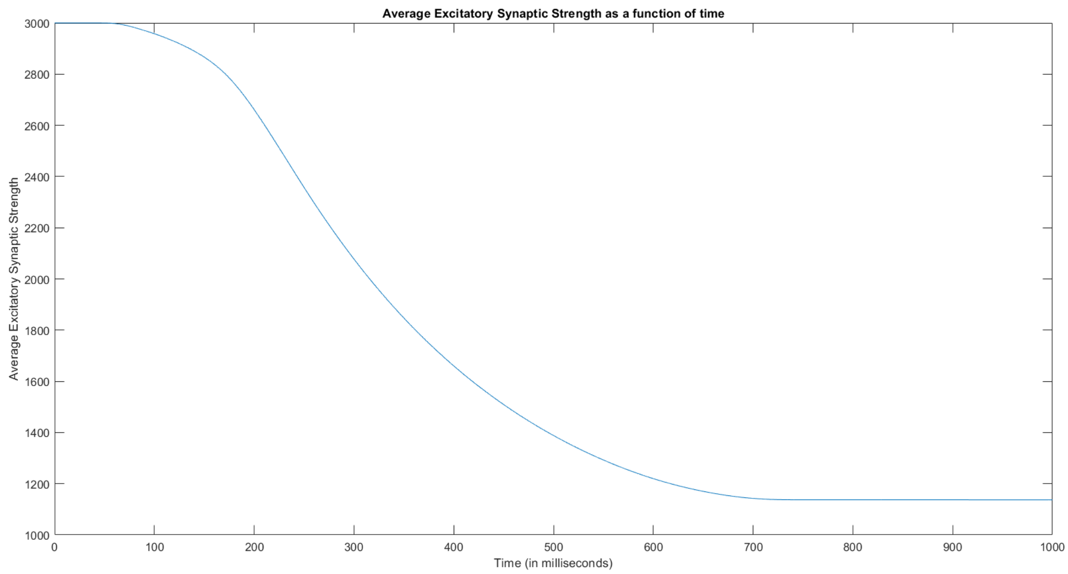

Figure 24: Average Excitatory Synaptic Strength vs. Time. Assuming anti-STDP (A_{up} = -0.01 and $A_{down} = 0.02$)