**Introduction**

This assignment is meant to simulate and examine the properties of additive and shunting networks. A network of ten cells will be the basis for the simulation. In the additive model, the effects of excitatory and inhibitory inputs are supposed to add linearly. The output firing rate of the presynaptic neuron is used. However, it is difficult to account for threshold and saturation effects within this model. Within a steady state, the firing rate depends heavily on the chosen weights.

The feedforward shunting model is more complex, allowing for the creation of a better neural network model. It can simulate more biological properties and has a wider dynamical range because it is derived from the Hodgkin-Huxley equation. In addition, shunting networks possess automatic gain control properties which ultimately make it capable to generate that wide dynamical range. The shunting model can also be modulated with additional terms that represent a distance-dependent receptive field. Therefore, this assignment will help us understand the advantages of creating a more complex model.

The skills that will be gained from this assignment are primarily within Matlab. Understanding the mesh function and plotting over a time interval instead of a steady state is more difficult. However, plotting the temporal dynamics over time will help with understanding the concepts that were learned in class. In addition, neuronal input is not always the same from different neurons. Therefore, being able to create a model that can take different inputs to see the result is relevant to understanding system's physiological limitations.

**Methods**

The feedforward additive network was simulated with the equation:

$$\frac{dx_i}{dt} = -Ax_i + BI_i - \sum_{k \neq i} I_k \qquad (1)$$

This equation represents the change over time for one neuron based on inputs from multiple others and its own activation. The $-Ax_i$ term is meant to represent the decay of the neuron in question. The $BI_i$ term is its excitation. Finally, the $-\sum_{k \neq i} I_k$ summation term is used to represent the surrounding neurons inhibitory effect on the neuron that is being looked at.

The feedforward shunting network was simulated with the equation:

$$\frac{dx_i}{dt} = -Ax_i + (B - x_i)I_i - x_i \sum_{k \neq i} I_k \qquad (2)$$

The main terms are kept the same, but with the addition of an $x_i$ term which represents the excitatory input coming from the neuron that we are looking at. This allows us to make the activity $x_i$ proportional to membrane potential.

Finally, the last network modeled was a modification of equation 2 with the addition of a distance-dependent receptive field to the shunting network.

$$\frac{dx_i}{dt} = -Ax_i + (B - x_i) \sum_{k=i-4}^{i+4} C_{ki} I_k - x_i \sum_{k=i-4}^{i+4} E_{ki} I_k \qquad (3)$$

The summation terms added here allows for neurons within the network to have proportional inhibition based on how far away they are from the neuron in question. This makes the system more physiologically sound as all inputs have different weights on each other.

Matlab was used for all equation simulation. Equation 1 and 2 were modeled within a steady state where $\frac{dx_i}{dt} = 0$ and solved for $x_i$, while equation 3 was modeled over time. Furthermore, the normalized STM activities for equation 1 and 2 were plotted as:

$$X_i = \frac{x_i}{\sum_{k=1}^{10} x_k} \qquad (4)$$

**Results**

Figure 1 and 2 both simulate equation 1 and 2 which are additive and shunting respectively. They show the expected results in terms of pattern. Figure 2 adds a time based component on shunting inhibition which shows that over time, the activity of a specific neuron will decrease.

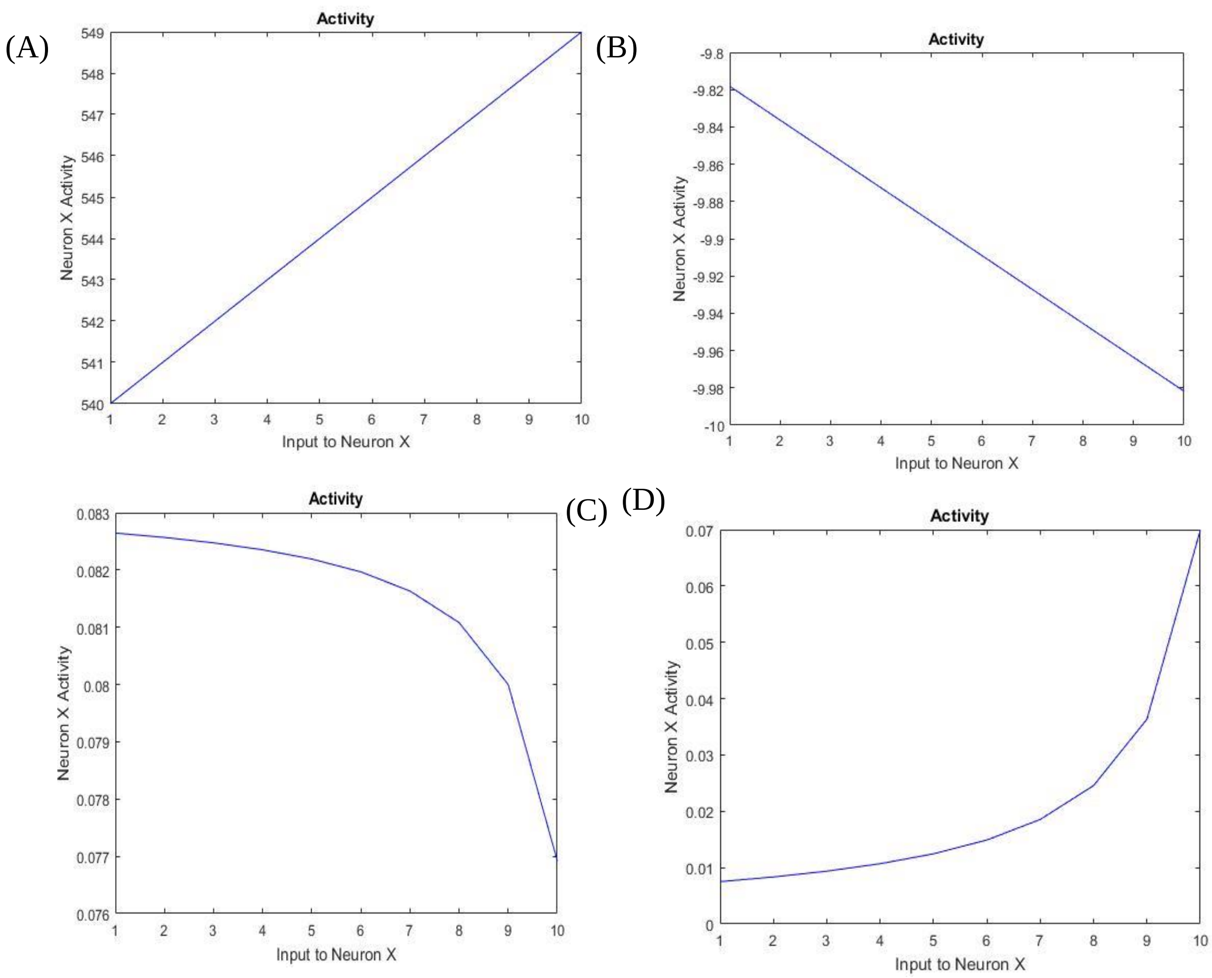



**Figure 1. Additive and Shunting Inhibition Equation modeling**. A) Shows the linear pattern of an input to a neuron as expected. It models equation 1. B) Models Equation 4 with Additive values to normalize STM activity. This shows that as the input decreases over time, the activity of neuron X decreases as well. C) Models equation 3 that shows that as input to a specific neuron decreases, the activity will decrease. D) Models equation 4 based on xi values from equation 3. Depicts inhibition increasing over time.

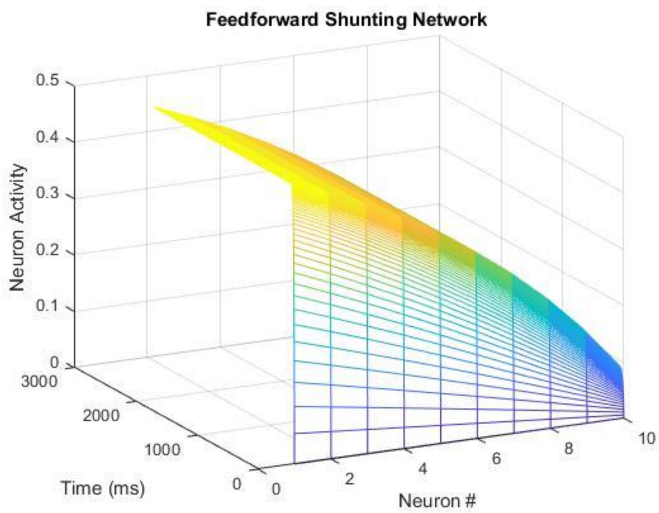
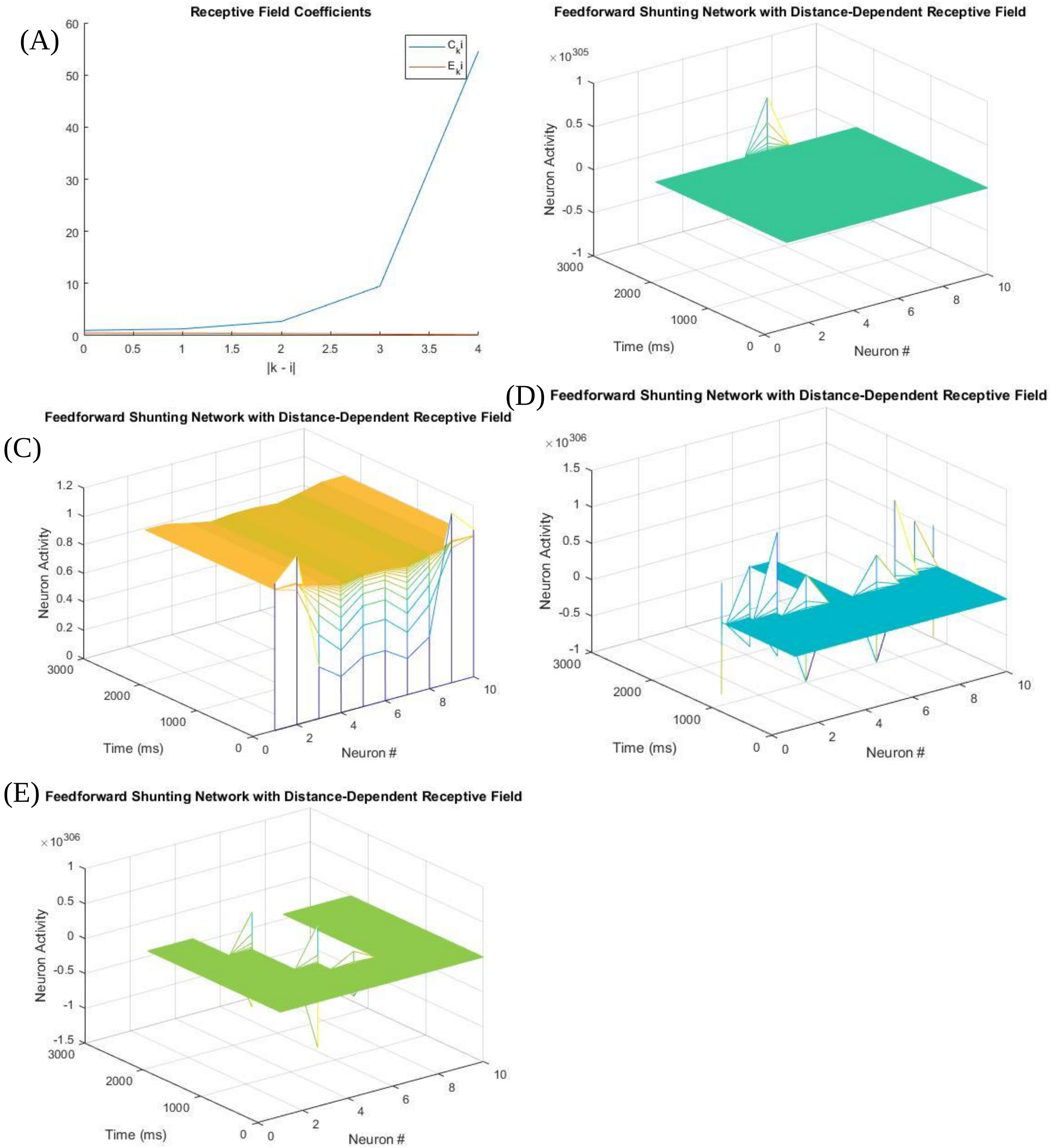



**Figure 2.** Feedforward Shunting Network over time. Depicts equation 2 based on its derivative, not solved in steady state.

Figure 3 as seen below explores the addition of a distance factor into equation 2, resulting in equation 4. Giving neurons different input patterns shows how distance impacts the neuronal activity.

**Figure 3**



**Discussion**

A)

In this case, we have an input I = {1.0, 0.9, 0.8, 0.7, … 0.1}. The additive network depicts a linear decrease over time as the stimulus pattern decreases over time as well. The upper and lower bounds on $x_i$ depend on the input. Therefore, when the input is 1 for one neuron, it will result in an upper bound being equal to the lower bound as it is an all or nothing response when all inputs are added. However, the shunting equation has distinct lower and upper bounds. When solved in steady state equilibrium, the $x_i$ upper bound is dependent on the input pattern. In this case the upper bound for $x_i$ is I = 1 because that is when the input for that specific neuron overpowers the active decay and the inhibitory connections coming from k neurons. The lower bound occurs when I = 0.1 at equilibrium because at steady state, the B value weight does not multiply the excitatory input to the point where it can summate more than the inhibitory inputs.

B)

If the rate of equilibration is given by the constant K that results in $e^{-Kt}$. The rate of equilibration within the additive network is dependent on the decay rate A and the summation of negative inputs. However, the summation of negative inputs from other neurons has the higher impact over time as A is just a constant. When the feedforward shunting network is solved in a steady state, the rate of equilibration of $x_i$ depends on the input and the summation of negative input.

$$x_i = \frac{BI_i}{A + I_i + \sum_{k \neq i} I_k}$$

Consequently, the rate of equilibration is dependent on the stimulus pattern because the input from other neurons leads $x_i$ to equilibrium.

C)

Modifying the additive equation and then solving for steady state results in:

$$x_i = \frac{BI_i - \sum_{k \neq i} I_k}{A + I_i}$$

This makes the upper and lower bound decrease as we take into account a proportional decrease when the input gets put in the denominator. Therefore, the rate of equilibrium increases due to adding another term in the denominator within the steady state. The networks equilibrium response will have a proportional decrease to the input.

D)

The addition of distance dependent coefficients allows us to look at the impact of different stimulus patterns. In this case, the further a stimulus is away from another neuron, the less impact it will have in the total summation. Four different stimuli were given:

A = { 0.1, 0.1, 0.1, 0.1, 0.1, 0.8, 0.8, 0.8, 0.8, 0.8 }
B = { 0.1, 0.1, 0.1, 0.1, 0.8, 0.8, 0.1, 0.1, 0.1, 0.1 }
C = { 0.1, 0.1, 0.8, 0.8, 0.8, 0.8, 0.8, 0.8, 0.1, 0.1 }
D = { 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0 }

Giving stimulus A is shown in Fig 3A where it shows a relative increase in neuronal activity within neuron 4-6, but other neurons on the outskirts do not see a summation of activity. When stimulus B is given in Fig 3B neurons 1-2 and 9-10 have a higher increase in activity because they are not being inhibited by surrounding neurons. When stimulus C is given, the neurons at the edge have a higher increase in activity. However, when a z-axis representing time is added, the duration of activity is longer in the middle neurons compared to the outer ones. (Fig 3D) Stimulus D is shown in Fig 3E, graphed in 2D and with a z-axis interpretation based on time. Firstly, we can see that the summation within the middle neurons have decreased activity. However, input summation will not necessarily be as strong due to distance, resulting in edge neurons having a higher activity. When the z-axis is added, we can see that duration of activity also correlates to the activity previously mentioned. More activity is sustained over time.

When compared to Figure 2 which models the shunting network over time, the addition of distance-dependent coefficients allows for the representation of a dynamic range adjustment based on input over time. Therefore, equilibrium is reached faster in a shunting network without those coefficients because the neuronal connections are equally weighted regardless of distance. When it is distance dependent, equilibrium should take longer to reach as the weights interact with the input pattern. For example, neuron 5 reaches equilibrium in 3seconds with stimulus C when modeled with the distance-dependent coefficients, but it takes a shorter time when modeled with equation 2.

**Summary**

Ultimately, the simulations show that the addition of physiological factors such as distance-dependent coefficients creates a more accurate system model. Furthermore, it shows that equilibrium is reached in a different time speed within a neuronal network based on what factors impact the rate of equilibration.