論文内容要旨

Heterogeneous axonal delay improves the spiking activity propagation on a toroidal network

不均質な軸索遅延は、トロイダル・ネットワーク上のスパイキング活動伝搬を改善する。

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INTRODUCTION

The human brain is an extraordinarily intricate neural network system, comprised of approximately 86 billion neurons and 85 billion non-neuronal cells. The diversity of these cells gives rise to various physiological rhythms that influence brain function [1] and gives rise to a wide array of cognitive abilities. This complexity also endows the brain with the capacity to adapt to new situations, reconfigure its organization, and maintain plasticity. Capitalizing on these properties, researchers have begun to apply the principles of neural networks to construct artificial intelligence systems. Contemporary neuroscience has witnessed significant progress in developing mathematical models that elucidate the biological mechanisms of dynamic systems that emulate brain function.

This development has been paralleled by the accumulation of substantial brain-related data, leading to a commensurate focus on mathematical computer simulations and their comparison with experimental results [2].

From a broader perspective, the brain functions within a noisy and heterogeneous environment [3], yet it remains unclear how the heterogeneity at neural and structural levels plays a vital role in brain functionality. In modern neuroscience, the proliferation of mathematical models has facilitated the recreation of dynamic systems mirroring the biological operations of the brain [4]. Within this context, stochastic resonance, an intriguing phenomenon in which embedded noise enhances a system's sensitivity and performance at a finite level, is believed to play a pivotal role in various natural and artificial neural systems [5]. Several studies demonstrate how stochastic resonance can significantly enhance signal detection [6-7].

This study seeks to contribute to the field by investigating the propagation of spike activity in a model network and developing a simple mathematical model that explains how heterogeneity can enhance signal propagation within neurons [8]. Notable examples include studies on transcranial random noise stimulation (tRNS), where subjects are stimulated with weak random electrical stimuli, resulting in improvements in motor, sensory, and cognitive tasks [9]. Given the inherent heterogeneity of the brain, we explore two types of heterogeneity in our study: axonal heterogeneity, related to variations in axonal distances between neurons, and neural heterogeneity, linked to differences in neuron dynamics. In real brains, neurons are not arranged in a regular grid but are influenced by randomness. In our model network, we manipulate axonal distances to create axonal heterogeneity, demonstrating that it enhances information propagation, termed the Stochastic Grid Enhancement (*SGE effect*). Neural heterogeneity, reflecting diverse characteristics among neurons within the same population or region, is critical in neuroscience as it sheds light on how different neurons contribute to brain function and information processing. Our study reveals that neural heterogeneity results in the most robust spiking activity, referred to as the Stochastic Neural Enhancement (*SNE effect*).

In this thesis, we demonstrate how the interplay between neural and structural heterogeneity enhances information propagation.

METHODS & RESULTS

Biologically speaking, neurons in the brain live in confined areas without specified borders. We choose a border-less structure as a torus to portray the most plausible representation of the brain's neuron population's network. The network is constructed from a 2D grid by connecting its borders to form a 3D torus. Each node/neuron communicates with its four adjacent neighbors as in figure 1.

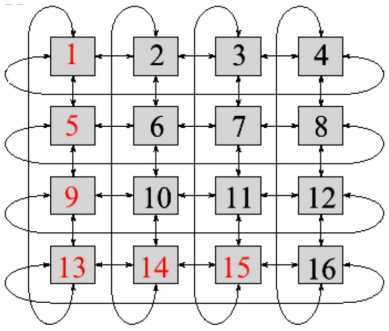


Figure 1.Each neuron has four connections and the border is connected to its counterpart.

The distance between nodes is calculated by the Manhattan distance (or taxicab geometry). As in figure 2, there may be several different paths with the same Manhattan distance between two points. Only a neuron, *initiator* n_{in} , is connected to a constant external current of $I = 10mA$ and spikes periodically. We analyze the signal propagation within the network to a random output neuron n_o by calculating the time it takes for the first spike to reach n_o. We ran several simulations while increasing the axonal heterogeneity.

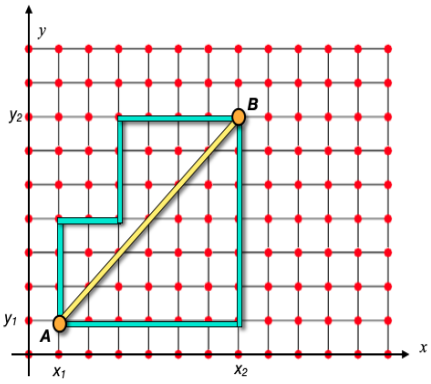


Figure 2.

In figure 3 is a biological representation of a neuron n_f connected to four neurons. The spike signals cross over the `axon` connection (*cd: central delay*) and the axon terminal (δ).

We define the sum of these two distance as *axonal transmission delay* $\mu = cd + \delta$, which is the connection between two neurons. The *cd* is the constant value of the axon while the variability of δ generates the axonal heterogeneity.

For each connection μ is calculated as : $\mu^{i,j}_{f,f_p} = cd^j + \overbrace{i\frac{cd^j}{ns}\times\left(2x^{i,j}_{f,f_p}-1\right)}$ (1) ;

where *ns* is an initial parameter and *i* represents the increment of the axonal heterogeneity $0 \le i \le ns$.

According to (1) :

for $i \to 0$ (small axonal heterogeneity) $\to cd\text{-}\varepsilon < \mu < cd+\varepsilon$

for $i \to ns$ (large axonal heterogeneity) $\to 0 < \mu < 2cd$.

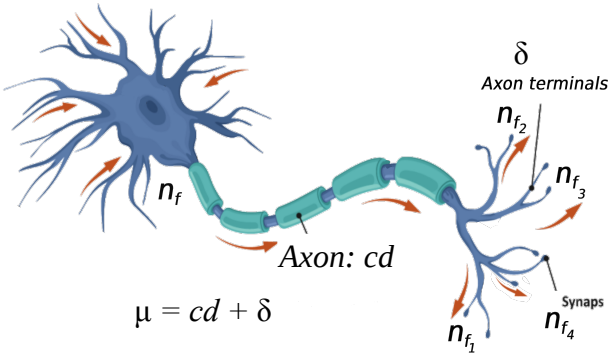


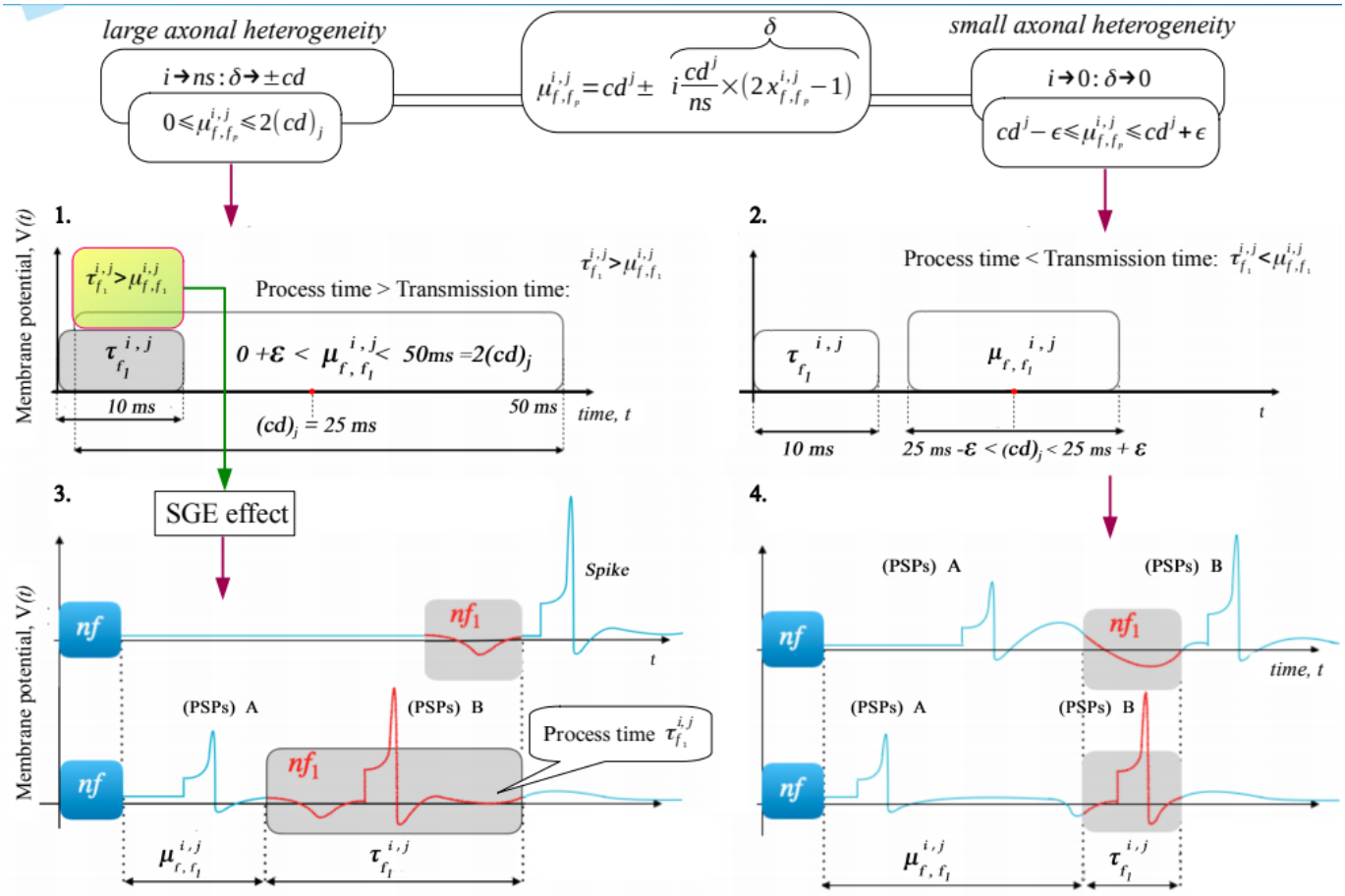
Figure 3.
Biological representation of intrinsic axonal delay between two neurons n_f and n_{fp} .

While μ represent the transmission time for a spike to run over the axonal connection ($cd + \delta$), we define the time it takes for the neuron to achieve a spike following the PSP as *process time* τ in ms.

Total propagation timed d

$d = \mu + \tau$ (axonal transmission time + process time).

Figure 4. Representation of the *SGE effect.*



In figure 4 panels 1, for $i \rightarrow ns$ (high axonal heterogeneity) if follows $0 < \mu < 2cd$, and it may happen that the process time $\tau > \mu$. When this happens, we may have a configuration as in panel 3. The neuron n_f is sending a PSPs **A** to the n_{fl}, while this is still processing a PSPs **B**. Since $\tau > \mu$, **A** will reach **B** inside n_{fl} to generate a spike. We call this the *SGE effect.*

In panel 2, for $i \rightarrow 0$ (small axonal heterogeneity), it results $\tau < \mu$ and no *SGE effect* takes action.

Therefore, the increment of axonal heterogeneity trigger the SGE effect which enhances spiking activity.

The neural heterogeneity is achieved by manipulating Izhikevich's model four parameters *a, b, c,* and *d.*

In figure 5, the combinations of the four parameters produced many types of neuron spiking behavior.

$$\begin{cases} v' = 0.04v^2 + 5v + 140 - u + I \\ u' = a(bv - u) \end{cases} \quad if\ v \geq 30\,mV \rightarrow \begin{cases} v \leftarrow c \\ u \leftarrow u + d \end{cases} \quad (2)$$

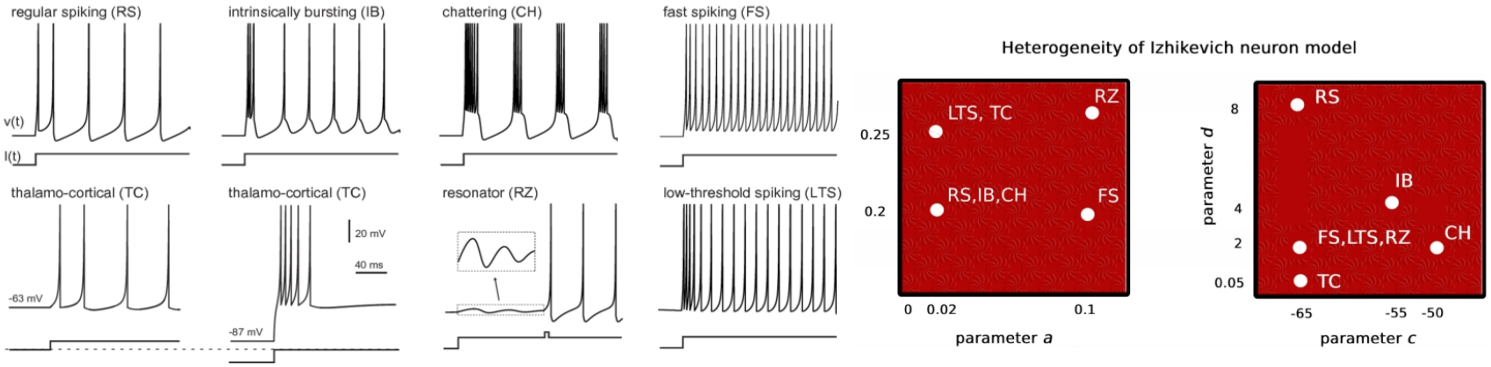


Figure 5. Neural heterogeneity. To the different values of *a, b, c, d* correspond a variability of a large range of neuron models.

In figure 6 a sketch of the effect of axonal heterogeneity over a single spike propagation. Each pixel's coordinate represents a neuron, and its color the time (or delay) of the first spike. The blue region is without spiking activity. The initiator n_{in} is stimulated with $I=10\ mA$. In panel B, to a larger axonal heterogeneity, corresponds a larger number of spiking neurons.

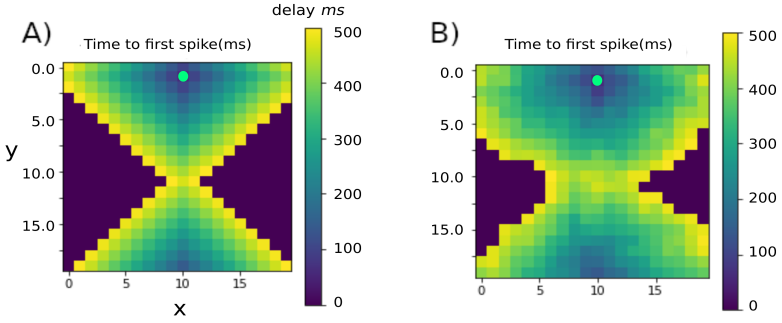


Figure 6. Single spike propagation.

We now define the *spike propagation delay* $\Delta f_o^{\,i,j}$ between n_{in} and n_o as: $\Delta f_o^{\,i,j} = f_o^{\,i,j} - f_{in}^{\,i,j}$

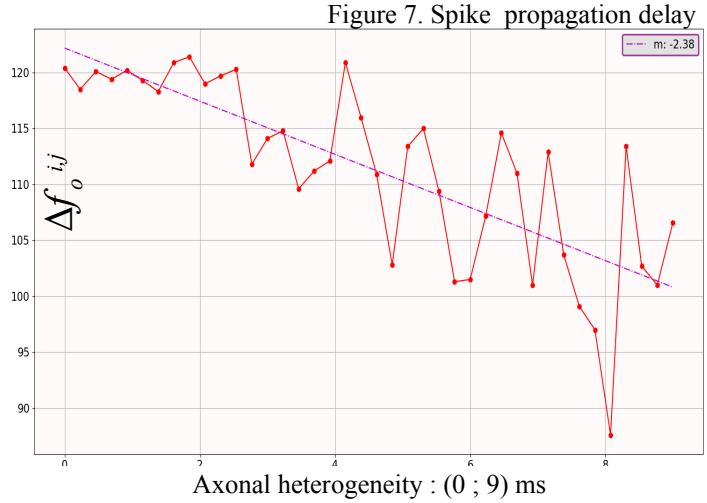
Figure 7. Spike propagation delay

$f_o^{\,i,j}$ and $f_{in}^{\,i,j}$ are the time of the first spike of n_o and n_{in}.

$i-loop$: increase the axonal heterogeneity of μ *(*constant cd^j).

$j-loop$: increase the value of the central delay cd^j .

In figure 7, the *y-axis* represents the $\Delta f_o^{\,i,j}$ values, the *x-axis* the axonal heterogeneity as *i* varies from 0 to 10 ms in *ns* steps for a $cd^j = 10\ ms$. As expected, by increasing the axonal heterogeneity, $\Delta f_o^{\,i,j}$ decreases due to the *SGE effect*. The value of the slop $m = -2.38$ confirms the decreasing of $\Delta f_o^{\,i,j}$.



According to the multinomial coefficient formula, by increasing the dimension of the network, the *SGE effect* get stronger. The pre-synaptic activity increases because the number of paths *P* with the same *mMd* from n_{in} to n_o increases. *P* is given by the *multinomial coefficient* → $P = \frac{(X+Y+Z)!}{X!\,Y!\,Z!}$.

In figure 8, a comparison of the *SGE effect* on three different dimensional ANNs. As cd^j varies from 1 to 71 *ms*, we calculate the value of *m* as the axonal heterogeneity increases in 40 steps as in figure 7. For each cd^j we plot three *m* for the 3D (blue), 4D (red), and 5D (green) network.

All *m* are negative, indicating the SGE effect, we notice that increasing the network dimension, as expected, the *SGE effect* strengthen up.

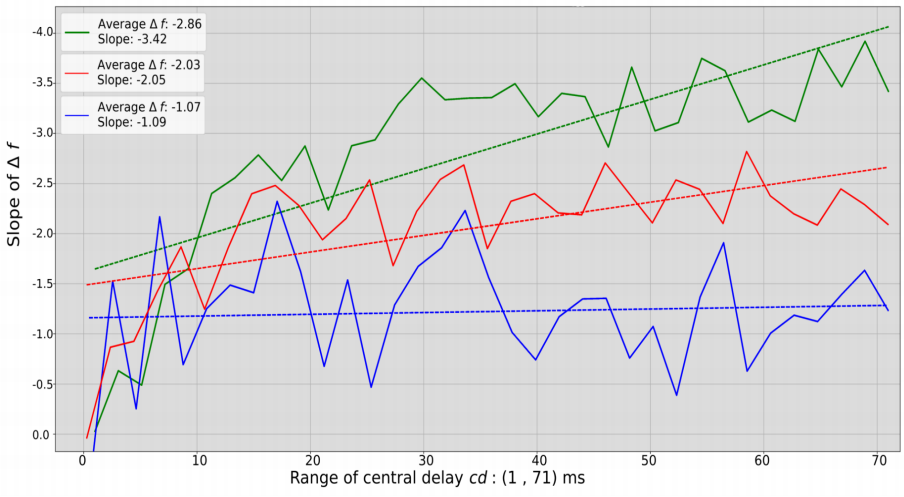


Figure 8. Comparison of regression's slope *m* for three-dimensional networks.

We achieve neuron heterogeneity by assign each excitatory cell n_i describe in (2) with the values:

$a_i = 0.02$, $b_i = 0.2$, $c_i = -65 + (15)\,x_4^{\,2}$; $d_i = 8 + (-6)\,x_5^{\,2}$, x_4 , x_5 : v. uniformly distributed in [0,1].

To $x_4 = x_5 = 0$ → regular spiking (RS) cell, and $x_4 = x_5 = 1$ → chattering (CH) cell. We use x_4 *and* x_5 x to bias the distribution toward RS cells (predominance cells).

In figure 9 we present the spiking activity for the same three different network of figure 8, under the combination of the axonal and neural heterogeneity.
The *cd* =22 ms as the axonal heterogeneity changes in 14 steps from o to 20 ms (*x-axis)*. The *y-axis* reports the number of total spike for the network.

The *neural heterogeneity* is represented by the six colored graphs. The blue graph indicates H=1 (100%) full neural heterogeneity, corresponding to a population of many different types of neurons. H= 0 (R.S.) zero heterogeneity indicates a network of all Regular Spiking neurons (R.S.). It can be observed as at any level of axonal heterogeneity the number of spikes for H=1 >> H=0.

Neural heterogeneity results in a larger spiking activity. We call this effect *stochastic neuron enhancement : SNE.*

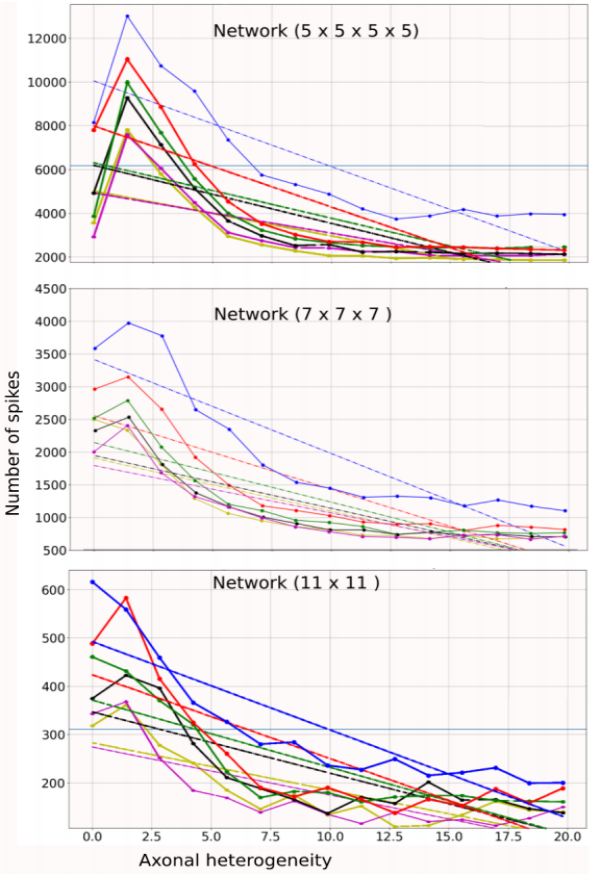


Figure 9. Spiking activity for three-dimensional networks.

Finally in the figure 10 and 11 we compare the result of the *SGE and SNE effect* as *cd ranges from 1 to 71* ms.
In figure 10 we show how the *SGE effect* acts in the same way for two models at 0 and full neural heterogeneity (H=0 red, and H=1 blue) . In the figure 11, however, for H=1 the network performs at the highest number of spiking activity.

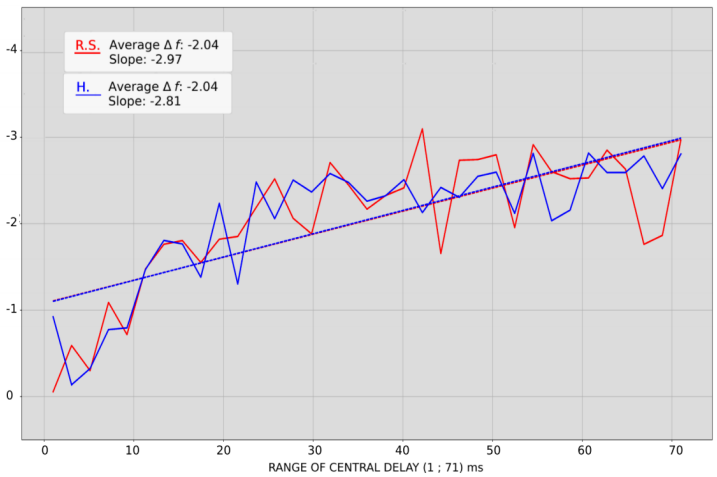


Figure 10. *SGE* effect of two models of neural heterogeneity H=1 and H=0.0

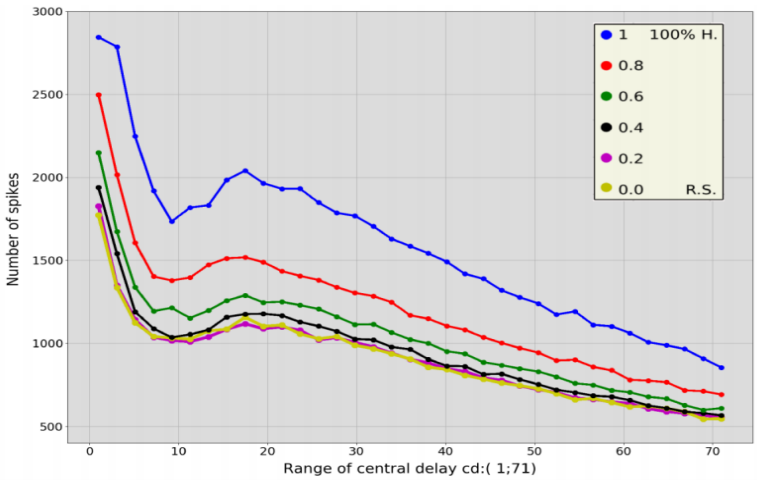


Figure 11. *SNE* effect. Spiking activity of H=1>> H=0 (R.S.).

We can conclude that, by keeping constant the current, synaptic strength, and the number of neurons, the right balance of axonal and neural heterogeneity offers the most suitable model regarding robustness (highest spiking activity, *SNE*) and spike propagation performance (*SGE* effect).

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