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RESEARCH ARTICLE

An Investigation of the Coefficient of Variation Using the Dissipative Stochastic Mechanics Based Neuron Model

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Abstract— In recent years, it has been argued and shown experimentally that ion channel noise in neurons can have profound effects on the neuron's dynamical behaviour. Most profoundly, ion channel noise was seen to be able to cause spontaneous firing and stochastic resonance.

A physical approach for the description of neuronal dynamics under the influence of ion channel noise was proposed recently through the use of dissipative stochastic mechanics by Guler in a series of papers. He consequently introduced a computational neuron model incorporating channel noise. The most distinctive feature of the model is the presence of so-called the renormalization terms therein. This model exhibits experimentally compatible noise induced transitions among its dynamical states, and gives the rose-Hindmarash model of the neuron in the deterministic limit.

In this paper, statistics of coefficient of variation will be investigated using the dissipative stochastic mechanics based neuron model.

Keywords— Ion Channel Noise; Stochastic Ion Channels; Neuronal Dynamic; Hindmarsh-Rose Model; Dissipative Stochastic Mechanism Model

I. INTRODUCTION

Neurons exhibit electrical action which is in nature known to be stochastic (Faisal 2008). The main source of stochasticity is the external noise from the synapses. Still the interior noise, which participates to the gating probabilistic nature of the ion channel, and also it can have important effects on the neuron's dynamic performance as displayed by the experimental studies (Kole 2006; Jacobson et al. 2005; Sakmann and Neher 1995) and by the numerical simulations or theoretical researches (Chow and White 1996; Fox and Lu 1994; Schmid et al. 2001; Schneidman et al. 1998).

Neuronal dynamics under the effect of channel fluctuation is usually modelled with stochastic differential equations acquired by using some vanishing white-noise conditions into the fundamental deterministic equations (Fox and Lu 1994). The dissipative stochastic mechanics (DSM neuron) based neuron model raised by Güler (2006, 2007, 2013), is a special case of this. The DSM model has some forms of functionality named the renormalization terms, as well as some vanishing white-noise conditions in the activity equations. The DSM model has been studied in numerical detail for its time independent input current's dynamics (Güler 2008, 2013); it was established that the corrections of renormalization increases the changes in behavior from quiescence to spiking and from tonic firing to bursting. It was further established that the existence of renormalization corrections can result in faster temporal synchronization of the electric coupled consecutive discharges of two neuronal units (Jibril and Güler 2009). In this thesis, the DSM model is investigated in the situation of noise

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fluctuating input currents and concentrates on what role the renormalization terms and noise could have on the spiking rates and the spike coherence values.

In neural membrane patches, spontaneous activity phenomenon occurs (in the case of repeating spikes or bursts) and the reason about that is the internal noise from ion channels; these present during numerical simulations of channel dynamics and theoretical investigations ((DeFelice, 1992); (Strassberg, 1993); (Lu, 1994); (Chow, 1996); (Rowat, 2004); (Güler, 2007); (Güler, 2008); (Güler, 2011) (Güler, 2013)); besides ,those experiments have shown the happening of stochastic resonance and the coherence of the procreated spike trains (Almassian A., 2011); (Jassim H. M., 2013) (Jung, 2001); (Schmid, 2001); (Özer, 2006)). Even when the numbers of ion channels are large, channel fluctuations might become critical near to the action potential threshold (Abdulmonim M. N., 2013); (Schneidman, 1998); (Rubinstein, 1995)); the small number of ion channels that are open at the action potential threshold assigned the accuracy of timing of action potential. Also it has been clarified that ion channel noise affects the spike generation in axons ((Faisal A. A., 2007); (Ochab-Marcinek, 2009)). The renormalization of the fluctuations in a number of open gates not only affects the neuron behavior, but also the attendance of a multiple number of gates in every ion channel. Moreover, this effect may indicates to an important act in cell activity in state of having coherence membrane in size (Güler, 2013).

II. NEURON STRUCTURE

Neurons are a specific kind of cells found in the human brain they're unique in generating electrical signals in reaction to chemical as well as other inputs. A normal nerve cell will be divided into three parts: the soma or cell body dendrites and axon. Dendrites receive inputs from other neurons cell and propagate it for the soma. The axon transmits the neuronal output to other cells. The dendrites structure is like a branch of a tree increases area cell from the branching structure which improves the capability of the neuron to receive a number of other cells through synapses connections. Figure1 explains details and structure for that neuron. Axons by single neurons traverse big brain's fractions or sometimes from the system. It is estimated that cortical neurons typically send about 40 mm of axon and also have approximately 4 mm of total dendritic cable into their structural dendritic trees. The axon makes an average of 180 synaptic connections to neurons per mm of length during the dendritic tree receives, normally 2 synaptic inputs per μm. The cell body or soma of the typical cortical neurons ranges in diameter from about 10 to 50 μm (Abbot, 2002).

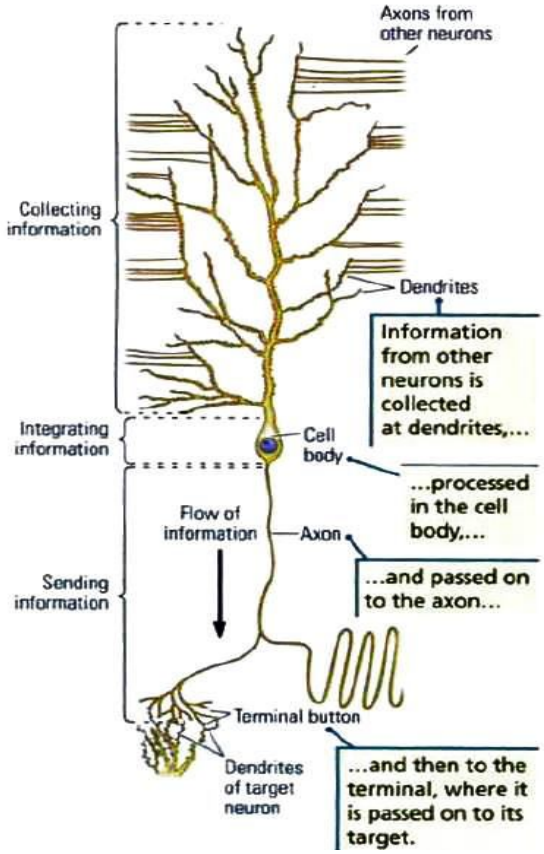

Figure 1: Two Interconnected Cortical Pyramidal Neurons (Izhikevich, 2007)

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III. MODELS

I.Hodgkin-Huxley Model:

Many scientists developed lots of realistic neural models depending on this model. Hodgkin and Huxley (1952) explain that the current passing through the axon of a squid has only two major ionic elements I_{Na} and $I_{k.}$.

According to the style of Hodgkin – Huxley that they explain the characteristics of electrical nerve patch membrane, as a possible equivalent circuit. In this patch all of the current across is manufactured of two basic sections: charging membrane capacitance may be the first one and the second is come with transport a particular type of ions via the membrane. Moreover the currents of ion are made of three unique elements, the potassium, sodium, and also the chloride. The current of sodium I_Na, the current of potassium I_K and the current of leakage I_L which can be related to chloride.

Depending on Hodgkin-Huxley electrical circuit the equation are going to be:

$$C_m \frac{dV_m}{dt} + I_{ion} = I_{ext} \qquad (1)$$

II. Hindmarsh-Rose Model:

FitzHugh and Nagumo (1961) observed separately in HH equations, that the improvements both in membrane potential V(t) and sodium activation m(t) happened in similar time scales during an action potential, whereas the change in sodium inactivation h(t) and also potassium activation n(t) are similar, although slower time scales. It can display the simulation of the model spiking behavior in the following equations:

(x) □=a(y-f_1 (x)+I)

y □=b(g_1 (x)-y)

Where x stands for membrane potential and y indicates the recovery parameter. f_1(x) is represented with cubic function, g_1(x) with linear function, variables a and b are time constants and that I(t) is the external current used or clamping while time function t. Hindmarsh-Rose taken advantage of the FitzHugh-Nagumo model to improve their model, that was a simple version of the (H-H) equations and substituted the linear function g(x) with a quadratic function so the model long interspaces interval can achieve rapid firing. Figure (4) shows the diagram of null-cline of the Hindmarsh-Rose model (Hindmarsh J.L. and Rose R.M 1982).

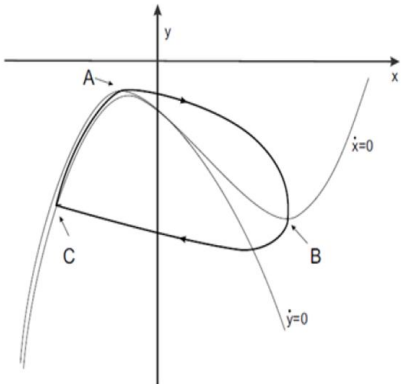

Figure 2: The 1982 HR model phase plane representation. Null-clines x □= 0, y □= 0 (thin lines) and firing limit-cycle (thick line). Design for one equilibrium node (Steur 2006).

III. Dissipative Stochastic Mechanics (DSM) Model:

The Dissipative Stochastic Mechanics based (DSM) neuron has a distinctive formulation that comes from a point of view that conformational changes in ion channels are exposed two different types of noise. Both of these types of noise were coined as the intrinsic noise and topological noise.

this is a special formulation comes from a point of view that ion channels fluctuation are subjected to two distinct types of noise (Güler 2006, 2007, 2008, 2013).

DSM neuron formula was created depending on Hindmarsh-Rose model (Hindmarsh and Rose 1984) and utilizes the Nelson's stochastic mechanics (Nelson 1966 and 1967), within the dissipation existence, to model the ion channel noise impacts about the membrane voltage dynamics. The topological noise influence on the

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neuron dynamics gets to be more crucial in membranes which are small in size. Accordingly, the DSM neuron functions like the Hindmarsh-Rose model if the membrane size is large.
The motion equations for both variables cumulates are resulted through the formalism from the DSM neuron. The second cumulates that depict the neuron's diffusive manners usually do not concern us within this thesis. The first cumulates develop harmoniously using the dynamics below:

$$m\dot{X} = \Pi + S_5 I \tag{2}$$

$$\dot{\Pi} = -\left(\frac{3a}{m}X^2 - \frac{2b}{m}X + S_0\right)(\Pi + S_5 I) - S_1 aX^3 + S_2 X^2 + S_6 X - S_3 X_{eq}(I) + S_1 I + S_7 - (1-r)[k\left(1 - \frac{\varepsilon_m^y}{m}\right)z + (1-k)\left(1 - \frac{\varepsilon_m^z}{m}\right)y \tag{3}$$

$$\dot{y} = -y - dX^2 + c + n^y \tag{4}$$

$$\dot{z} = -rz + rh(X - x_s) + n^z \tag{5}$$

$$\Pi(t_0) = y(t_0) - z(t_0) - a\left(X(t_0)\right)^3 + b\left(X(t_0)\right)^2 + (1 - S_5)I(t_0) \tag{6}$$

where X indicates the membrane voltage value expected, and Π matches towards the arithmetic mean of the momentum-like operator. Variables y and z describe the short and also the slower ion dynamics, respectively. I represent the outside current inserted in to the neuron, and m represents the capacitance on the membrane. The variables a, b, c, d, r, and h are constants. K is really a mixing coefficient presented by k = 1/(1+r). S_i are constants as shown next:

$$S_0 := k + (1-k)r \tag{7}$$

$$S_1 := S_0 - [k\frac{\varepsilon_m^y}{m} + (1-k)r\frac{\varepsilon_m^z}{m} \tag{8}$$

$$S_2 := k\left(1 - \frac{\varepsilon_m^y}{m}\right)(b-d) + (1-k)\left(1 - \frac{\varepsilon_m^z}{m}\right)(rb-d) \tag{9}$$

$$S_3 := k\varepsilon_u^y + (1-k)\varepsilon_u^z \tag{10}$$

$$S_4 := k\frac{\varepsilon_m^y}{m} + (1-k)\frac{\varepsilon_m^z}{m} \tag{11}$$

$$S_5 := 1 - S_4 \tag{12}$$

$$S_6 := S_3 - S_5 rh \tag{13}$$

$$S_7 := (rhx_s + c)S_5 \tag{14}$$

Eq. (6) defines Π value at the beginning time t_0 in terms of the beginning values of the other dynamical parameters *X*, *y* and *z*, and the current *I*. *Xeq(I)* bows to the equation:

$$aX_{eq}^3 - (b-d)X_{eq}^2 + h\left(X_{eq} - x_s\right) - c - I = 0 \tag{15}$$

Where x_s is a constant. n^y and n^z in Eqs. (4) and (5) are noises from the Gaussian white kinds with zero means and mean squares presented by:

$$< n^y(t)n^y(t') >= 2mT\delta(t-t') \tag{16}$$

And

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$$< n^z(t)n^z(t') >= 2rmT\delta(t-t') \quad (17)$$

are obtained by the fluctuation-dissipation classical theorem. T Indicates a temperature like value. The renormalization terms are the conditions with the correction coefficients ε_m^y ,ε_u^y, ε_m^z and ε_u^z that occur in the equations above, all the parameters in this model are in dimensionless unit.

When the epsilon values reaches values that are larger than (ε_m^y=0.3, ε_u^y=1.5, ε_m^Z=0.003, and ε_u^Z=0.015) that is when the neuron reach the saturation states.

When the noise parameters $\mathbf{n}^y$ and $\mathbf{n}^z$ are neglected and setting all of the correction coefficients to zero, the dynamics from the DSM works such as dynamics of Hindmarsh-Rose. All of the model parameters, even time, have been in dimensionless units. The initial voltage time number of the membrane for Hindmarsh-Rose's original model. Hindmarsh-Rose model dynamical states are quiescence, bursting (rhythmic using a periodicity in high degree, or chaotic), and tonic firing.

It was shown that the representation of intrinsic noise will get to be more important in small size membranes and it's the same in case of fewer channels in DSM Neuron (Güler 2008). The intrinsic noise can be the source of spiking activity in quiet deterministic model and in large input current values bursting can be caused. he DSM Neuron dynamics in a small size membrane is demonstrated. Notice that renormalization corrections are equal to zero so that the result is studied regardless of the topological noise influence.

IV. NUMERICAL EXPERIMENTS

In our investigation we examine the role played by the renormalization terms and to be exact the effect of the epsilons value on the neuron. We change the epsilons values many times and compare between them to see the epsilons values on the neuron.

The model's behavior is studied within the following ranges of the parameters: We used

input current values between (1-7) and the other experiments the input current was (7-11). In the first experiment the default epsilons values as in Label (A) in Table (1) is used and by changing the input current from (1-7) we get the first set of result, after that we used the epsilons values as in Label (B) in Table (1) and did the experiment again to get the second set of result and finally we make the epsilons values equal to zero as in Label (K) in Table (1) and did the experiments again so we can get the third set of result to draw the result that in the figure (3) below.

After that we change the default epsilons values and take four new epsilons values that will replace the default epsilon value in the first experiment. The first two epsilon values are smaller than the default epsilon values and there values are multiplied be 0.5 and 0.8 as in Table (1) (Label C and E respectively), we draw the three result while changing the input current, the first set when the epsilon values are zero as in Label (K) in Table (1),the second set when the default epsilon value are multiplied by 0.5 and 0.8 as in Table (1) (Label C and E respectively) and the last set when we used epsilon values as in Label (C) in Table (1) and we collected the result as in the figures (4) and the figure (5) for the default epsilon value as in Label (E) in Table (1).

Now the second two epsilon values which are larger than the default epsilon values and there values are calculated by multiplied the default epsilon value be 1.3 and 1.5 and there values are in Table (1) (Label G, I respectively), the first set of result is calculated when the epsilons values are zero as in Label (K) in Table (1), the second set when the default epsilon value are multiplied by 1.3 and 1.5 as in Table (1) (Label G, I respectively), the last set of result when we used the epsilons values as in Label (H) in Table (1) the results are drown in the figure (6) and figure (7) for the default epsilon value when we used it as in Label (J) in Table (1).

Table 1: Parameter sets of the epsilon values used in the thesis

LABEL	Multiply the default by	ε_m^y	ε_u^y	ε_m^z	ε_u^z
A	Default (0.1)	0.1	0.5	0.0001	0.0005
B	Double (0.1)	0.2	1	0.0002	0.001
C	0.5	0.05	0.25	0.0005	0.0025
D	Double (0.5)	0.1	0.5	0.001	0.005
E	0.8	0.08	0.4	0.0008	0.004
F	Double (0.8)	0.16	0.8	0.0016	0.008

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G	1.3	0.13	0.65	0.0013	0.0065
H	Double (1.3)	0.26	1.3	0.0026	0.013
I	1.5	0.15	0.75	0.0015	0.0075
J	Double (1.5)	0.3	1.5	0.003	0.015
K	Zero	0	0	0	0

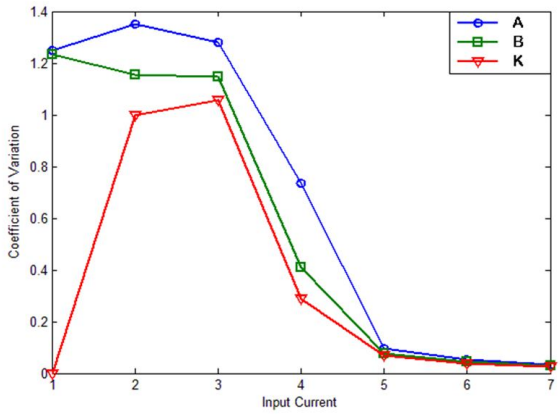

Figure 3: The Coefficient of Variation against the Input Current. The Three Plots are Shown the Labels (A), (B), and (k) Parameters as in the Table (1).

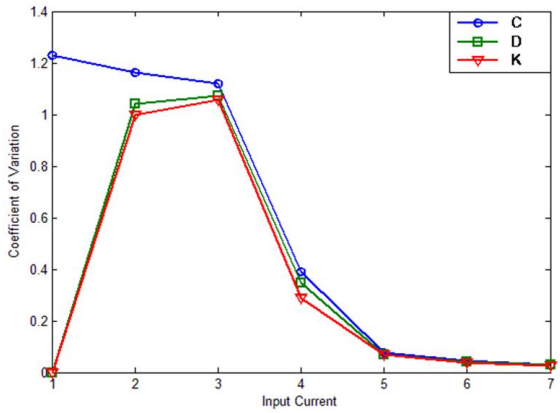

Figure 4: The Coefficient of Variation against the Input Current. The Three Plots are Shown the Labels (C), (D), and (k) Parameters as in the Table (1).

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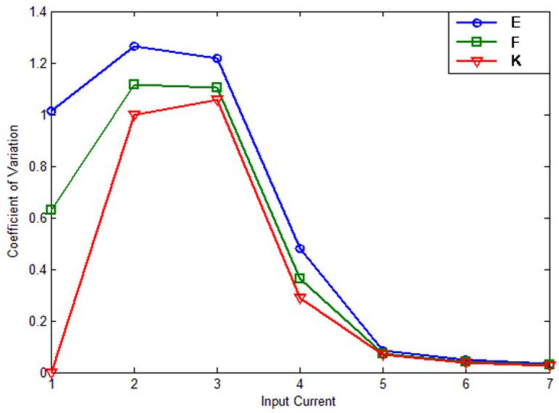

Figure 5: The Coefficient of Variation against the Input Current. The Three Plots are Shown the Labels (E), (F), and (k) Parameters as in the Table (1).

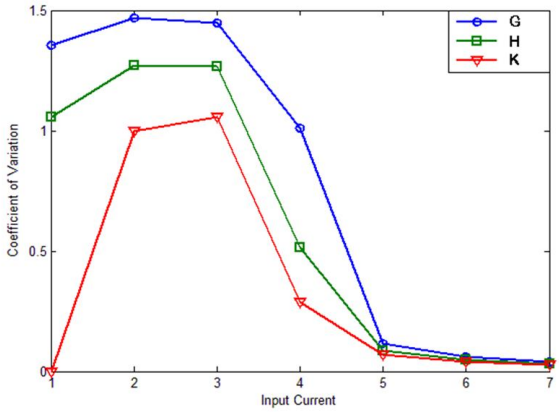

Figure 6: The Coefficient of Variation against the Input Current. The Three Plots are Shown the Labels (G), (H), and (k) Parameters as in the Table (1).

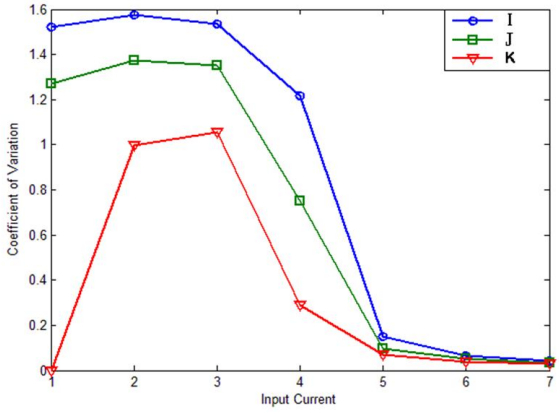

Figure 7: The Coefficient of Variation against the Input Current. The Three Plots are Shown the Labels (I), (J), and (k) Parameters as in the Table (1).

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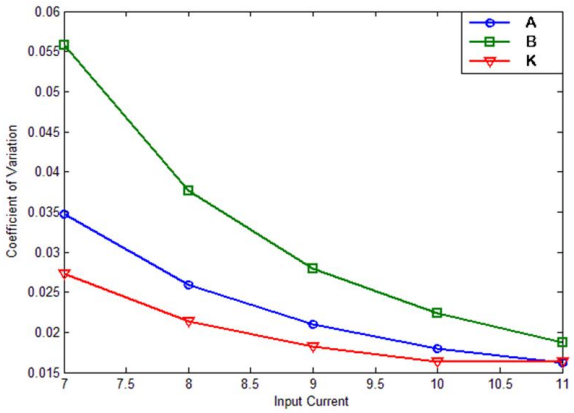

Figure 8: The Coefficient of Variation against the Input Current. The Three Plots are Shown the Labels (A), (B), and (k) Parameters as in the Table (1).

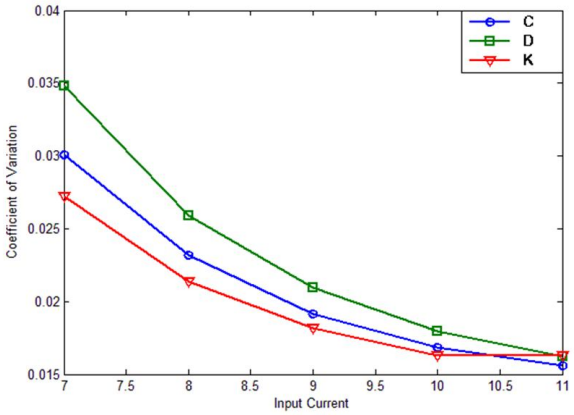

Figure 9: The Coefficient of Variation against the Input Current. The Three Plots are Shown the Labels (C), (D), and (k) Parameters as in the Table (1).

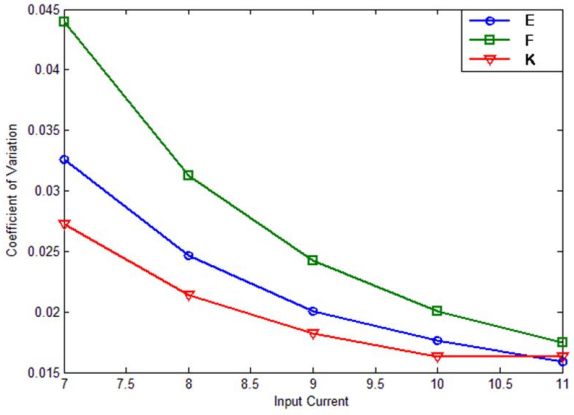

Figure 10: The Coefficient of Variation against the Input Current. The Three Plots are Shown the Labels (E), (F), and (k) Parameters as in the Table (1).

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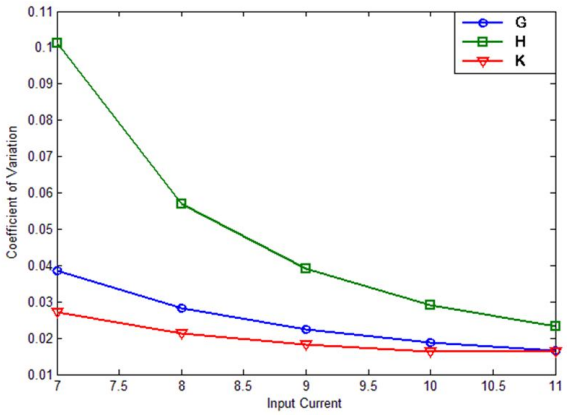

Figure 11: The Coefficient of Variation against the Input Current. The Three Plots are Shown the Labels (G), (H), and (k) Parameters as in the Table (1).

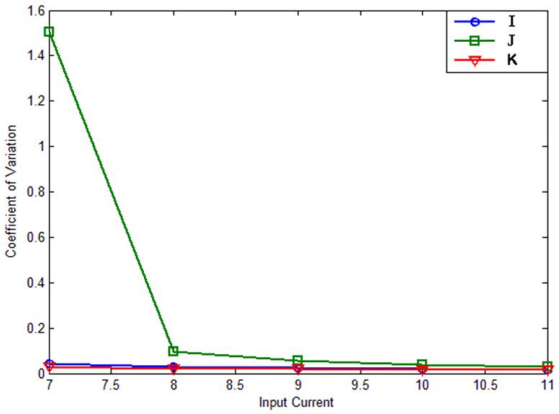

Figure 12: The Coefficient of Variation against the Input Current. The Three Plots are Shown the Labels (I), (J), and (k) Parameters as in the Table (1).

In the experiments in figures (3 to 7) the input current was from (1-7) and because of that the effect of the epsilon values makes the double epsilon values to go under the default epsilon values. When we compare the default epsilon values in figure (3) with the two epsilon values that are smaller than the default epsilon values that we got the first epsilon values as in Label (C) in Table (1) and the second epsilon values as in Label (E) in Table (1) the epsilon values effect will start reducing. However, when we compare the default epsilon values as in figure (3) with the two epsilon values larger than the default epsilon values will be in the first one as in the Label (G) in table (1) as in figure (6) and the second one will be as in Label (I) in Table (1) as in the figure (7) the effect of the epsilon values will start to increase as the epsilon values increase.

After that we change the input current from (1-7) to (7-11) and compare the default epsilon value in figure (8) with the two epsilon values smaller than the default epsilon value as in Label (C , E) in Table (1) for figure (9) and figure (10) respectively we found out that the influence of the epsilons values was reduced compere with default value. After that when we compare the default epsilon value in figure (8) with the other two epsilons values that are larger than the default epsilon value which we have them from the Label (G , I) in Table (1) for figure (11) and figure (12) respectively and the input current from (7-11) we realized that the impact of the epsilons values start to increase and that makes the neuron lose its properties and after a while when the increase the epsilon values higher the neuron starts to become ineffective until the increase passes the value ($\varepsilon_m\hat{}y=0.15$, $\varepsilon_u\hat{}y=0.75$, $\varepsilon_m\hat{}Z=0.0015$, and $\varepsilon_u\hat{}Z=0.0075$) when its double reaches values that are larger than ($\varepsilon_m\hat{}y=0.3$, $\varepsilon_u\hat{}y=1.5$, $\varepsilon_m\hat{}Z=0.003$, and $\varepsilon_u\hat{}Z=0.015$) when the neuron reaches the saturation states.

Our result shows that we the default epsilon value is much better to be use when dealing with the DSM neuron.

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V. CONCLUSIONS

In this thesis, the DSM neuron model was investigated from a numerical point of view when exposed to renormalization terms. The impacts of the epsilon values on the neuron were checked. Correction coefficients were used as an effective measure of renormalization corrections to the model. It should be considered that these renormalization corrections appear from the dilemma of being in doubt of how many open ion-channel numbers there are, even if we know the exact number of open gates.

DSM model neurons appear to be more complex than other models. It shows quicker synchronizing between two DSM neurons (Jibril and Güler 2009), dynamics of the models under constant input currents (Güler 2008) and in addition, its ability in detecting signals under noise varying and periodic input currents, that have been inspected during this study, are all the model benefits that deserve tolerating the complexity of it. Furthermore, it should be taken into consideration that this model is extremely capable of handling the small membrane sizes of the neurons.

The experiment show that the renormalization terms effects play a role on the value of coefficient of variation for a small input current but for large input current there is no effect.

The epsilon values shown when the input current are large, there is no effect because the spike increasing high, so between two spike events the renormalization effect do not have time to show themselves because before the time show the effect, another spike start. But when the input current is small the spike low, so there is a stabile time for renormalization to show the effect.

The experiments show that the epsilon values plays important role. The absence of the epsilon values makes the neuron generate spikes in slow manner and makes it have the lowest coefficient of variation.

The existence of the epsilon values when the input current is higher than (7) makes the neuron react better and have higher coefficient of variation compare to the case when the epsilon value equal to 0 as in figures (9) to (12).figures(3 to 7) show that when the input current is lower than (7) the neuron react the same as before however it defer only when we double the epsilon values it result will goes under the result of the default value because of the effect of the epsilon values.

The results reveal that the neurons are extremely able to make a complicated and advantageous use of the channel noise in handling signals. From a technological point of view, the study shows that the DSM model has promising potential for signal detection.

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