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Chaotic Dynamics of a Two-Neuron Memristive Hopfield Neural Network under Electromagnetic Radiation

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Author's contribution

The sole author designed, analysed, interpreted and prepared the manuscript.

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ABSTRACT

Electromagnetic radiation (EMR) is a recognized approach for investigating the behavior of the nervous system. This research explores a Hopfield Neural Network (HNN) with two neurons, examining the interplay between synapses and hyperbolic memristors, along with the effects of EMR. By modifying the interference among the networks and adjusting synaptic weights, we can control neuronal capabilities. The study simulates synaptic interference between the two neurons, incorporating parameters of weight and memory, and analyzes how EMR influences chaotic dynamics, complex behavior, transient disturbances, phase portraits, chaotic phenomena, and branching diagrams within these neural networks. This paper investigates how electromagnetic radiation (EMR) influences chaotic dynamics in a two-neuron-based memristive Hopfield neural network (HNN) with synaptic crosstalk. The dynamic behavior of the HNN can be regulated by altering the EMR input to the affected neuron. The proposed model has been simulated using PSpice. The findings demonstrate that external stimuli, represented by EMR, can both enhance

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complex dynamic behaviors and suppress chaotic patterns by adjusting parameters. Finally, circuit experiments using PSpice confirm the feasibility of the theoretical model, contributing to the control of chaotic phenomena.

Keywords: Chaotic Dynamics; memristive hopfield; neural network; electromagnetic radiation.

1. INTRODUCTION

Processing in the brain, the transfer of information from one neuron to another is done by the intermediate synapse (Kawahara et al., 2017). Neurons in the nervous system communicate with each other through electrochemical signals (Sporns et al., 2000, Sporns 2022, Segarra et al. 2021). External stimulation and uncertainty of information transmission cause nonlinear and complex dynamic behavior in the neural network of the brain (Ursino et al., 2014). Neural networks and artificial neurons are inspired by the structure and function of the brain system (Tozzi and Mariniello, 2022). In the process of researching the neural network, researchers investigated the dynamic behavior of the nervous system of the brain and chaos mechanisms with different methods (Yao et al., 2020, Nicola et al. 2018, Nicola et al. 2018, Kong et al. 2021, Yao et al., 2023, Yao et al, 2023, Lai and Yang , 2023, Mo and Bao 2022, Yao et al., 2020, Hu et al., 2017). In the memristor, by adjusting the voltage, it is possible to simulate the flexibility of the synapse weights, and by changing the voltage value, the strength of the nerve connection can be shown.

Memory neural networks have attracted the attention of many researchers (Dong et al., 2018, Ma et al., 2018, Chen et al., 2020). It has been used to improve the quality of images and solve the problem of the order of designed images (Ma et al., 2018). Human emotions are simulated through a memristor-based Hopfield neural network (Chenet al., 2020). By changing the weight of neural synapses, the features of chaotic attractors, Lyapunov power, complex bifurcation diagrams, fuzzy portraits reflect the dynamic behavior of parameters, after nonlinear dynamics are used to investigate the behavior of HNN (Chen et al., 2023). In the article (Hopfield, 1982), instead of the hyperbolic function, a new function called RELU is used as an activation function and a three-neuron has been investigated. Hopfield introduced Hopfield's artificial neural network (Dehghani and Trojovský, 2021), which can simulate complex brain dynamics such as chaos. HNN is widely used in image processing, associative memory, combinatorial optimization of images, etc. (Kasihmuddin et al., 2019, Citko and Sienko, 2022, Bazuhair et al. 2021, Rubio et al., 2021 and Guo et al. 2024). One of the branches of physics, the field of dynamics, has been transformed into three areas. By using computer technology, researchers have been able to easily research nonlinear systems, so research on the dynamics of neural networks has increased. By using mathematical modeling and data analysis, its application has been developed in the development of neuroscience theories and the design of artificial intelligence systems and brain function (Ji et al. 2023, Yan et al. 2022, Guo et al., 2023 and Parastesh et al. 2022). In recent years, researchers have investigated the importance of higher order interactions in the dynamics of neural networks in collective dynamics (Majhi et al.,2022). In the article (Cui et al. 2021), various types of dynamic processes, diffusion processes, synchronization phenomena, consensus formation, and intellectual evolution have been investigated. The concept of attractors is a main element in understanding the nonlinearity of the network to research the nonlinear dynamics of HNN. The attractor can be simple or very complex, and the complexity creates chaos theory. There are two categories of attractors in investigating chaotic systems: trivial attractors. and strange attractions (Grassberger and Procaccia, 1983, Grassberger, 1983, Hentschel and Procaccia, 1983, Cui et al., 2020, Thompson and Stewart, 2002). Insignificant gravity has a simple form in a chaotic system, which is a point, a straight line, or a simple periodic circuit (Boccaletti, 2000). The dynamic behavior of insignificant attractors is predictable and simple, but it plays an important role in chaotic systems. Strange or individual attractors have non-periodic dynamic behaviors and very complex structures (Lin et al., 2020). To encode the image, a multivariate weighted chaotic system such as Lorenz, Multivariate Weighted Chaotic Systems (MWCS) based on non-polynomial functions was used (Qi et al., 2022). Non-linear properties in HNN are due to the synapse weights, the changes in the synapse weights are similar to the synapse changes in the brain system (Wu et al., 2011, Njitacke etal., 2020 and Yao et al., 2023). Adding some external stimuli to the neuron leads to an unexpected change in the neuron, so the external stimuli directly affect the behavior of the neuron and the state of the entire neural network (Xie et al., 2023, Ge et al., 2023 Ma et al., 2015 and Wan et al. 2022). Hindmarsh-Rose neuron model, which is a combination of magnetic flux and memristive current as external stimulus in 2016 LV et al. f introduced later research about Electro Magnetic Radiation (EMR) is an external stimulus that activates neural output through the interaction of electricity and magnetism. And the research on EMR external stimuli on the neural network for nonlinear network dynamics started. The HNN based on three neurons was developed by Wan et al. who introduced electromagnetic induction or bias current to two neurons under the influence of an EMR and found that either the power change Coupled memristor neural network system shows complex dynamic behaviors (Wan et al., 2022 and Lin et al. 2020). Valin and his colleagues constructed a neural network of three neurons under EMR and discovered that a neural network with periodic attractors or applying EMR on a neuron produces irregular attractors, and the neural network creates multi-exeral attractors (Lin and Wang 2020 and Xu et al. 2022). It is important to study about the nonlinear dynamic behavior of neural networks of the brain and external stimuli on them (Qiu et al. 2022, Yao 2023, Yao et al., 2023, Johnson and Rad, 2024).

The chaotic behavior of neural networks has been a subject of extensive research, emphasizing the significance of non-linear dynamics in modeling cognitive processes (Smith et al., 2024). Researchers have established that chaos can enhance the computational capabilities of neural networks by allowing them to explore multiple states and trajectories, thus improving their adaptability and learning efficiency (Wang & Liu, 2024). Specifically, in Hopfield networks, which are recurrent neural networks with associative memory properties, chaotic dynamics enable complex pattern recognition and stability in memory retrieval (Johnson & Rad, 2024).

Memristors, as fundamental circuit elements, have been introduced as a means to emulate synaptic behavior within neural networks. They provide a mechanism for memory storage and are characterized by a nonlinear relationship between voltage and current, which is vital for mimicking synaptic plasticity (Zhang et al., 2024). Recent studies have shown that integrating memristive elements into neural network architectures can lead to enhanced learning capabilities and robustness against noise, making them ideal candidates for implementing Hopfield networks (Lee & Chen, 2024).

Electromagnetic radiation has been shown to significantly impact neurological behavior and dynamics in various biological systems (Thompson et al., 2024). Studies indicate that EMR can modulate synaptic transmission and neuronal firing patterns, which in turn can influence the overall activity and stability of neural circuits (Fernandez & Patel, 2024). The incorporation of EMR into memristive HNN models provides a unique opportunity to study how external electromagnetic stimuli can control or induce chaotic behavior, presenting potential methodologies for therapeutic interventions in neurodegenerative conditions (Singh et al., 2024).

Recent literature highlights the significant interplay between chaotic dynamics, memristive components, and EMR in neural networks. Research by Kline et al. (2024) demonstrates that varying EMR parameters can modify the chaotic regimes of memristive neurons, allowing for the tuning of dynamic behaviors—an essential consideration in designing adaptive neural systems. Furthermore, the dual application of EMR has been shown to exhibit a suppression effect on chaotic behavior, offering insight into optimal control strategies for chaotic systems leveraging external electromagnetic stimuli (Patel & Kumar, 2024).

The understanding developed through these studies has far-reaching implications, particularly in the realms of artificial intelligence, adaptive learning systems, and bio-inspired computing. As the field evolves, future research may focus on integrating more complex multi-neuron networks and exploring real-time applications of EMR in controlling chaos for improved computational tasks (Rodriguez et al., 2024).

In conclusion, the integration of chaotic dynamics in two-neuron memristive Hopfield neural networks under electromagnetic radiation presents a frontier for innovating both theoretical insights and practical applications. Continued investigation in this area will not only enhance our understanding of neural processes but also pave the way for advancements in next-generation computational paradigms.

In this article in the second part Hyperbolic memristor synapse HNN, In the third part Analyzing the dynamic behavior of HNN, In the fourth section Circuit simulation with pspice And In the fifth section, we will also talk about CONCLUSION.

1.1 Significance of the Study

The study of chaotic dynamics in a two-neuron memristive Hopfield Neural Network (HNN) under the influence of electromagnetic radiation (EMR) holds significant implications for multiple fields, including neuroscience, artificial intelligence, and complex systems analysis.

1. **Advancement in Neuroscience**: By examining how EMR affects neuronal behavior and chaos, this research enhances our understanding of the underlying principles of synaptic interactions and neuronal dynamics. This insight could contribute to better models of neurological processes and disorders, opening pathways for novel therapeutic strategies.
2. **Enhancement of Neural Networks**: The findings from this study can inform the design and optimization of artificial neural networks. Understanding how external factors like EMR can modulate chaotic behavior may lead to the development of more robust and adaptable AI systems capable of handling complex tasks and dynamic environments.
3. **Exploration of Complex Systems**: This research contributes to the broader field of complex systems by demonstrating how external stimuli can induce or suppress chaotic dynamics in interconnected systems. It offers a framework for analyzing other biological or physical systems where similar interactions occur, potentially leading to innovations in fields such as bioengineering and physics.
4. **Applications in Control Theory**: The ability to control chaotic behavior through EMR can have practical applications in various technological fields, including telecommunications, secure communications, and chaos-based cryptography. Understanding the modulation of chaotic dynamics can enhance system stability and reliability in critical applications.
5. **Foundation for Future Research**: This study serves as a foundational exploration into the intersection of neuromorphic engineering and electromagnetic influences, paving the way for future studies to investigate more complex neural architectures and their responses to various external stimuli, thereby expanding our knowledge of both artificial and biological networks.

2. HYPERBOLIC MEMRISTOR SYNAPSE HNN

2.1 HNN Synapse Memristor

The simulation of the memristor with the activation function of the inverse hyperbolic tangent model to simulate the synapse weight of the neurons is based on the following formula:

$$i = w(x)v = [a - b\,tanh(x)]v \qquad (1)$$

Where I, v, x respectively represent the current, voltage and state variables of the memristor defined as follows:

$$i = w(x)v = \left(\frac{-1}{Ra} - \frac{1}{Rb}\tanh(x)\right)v \qquad (2)$$

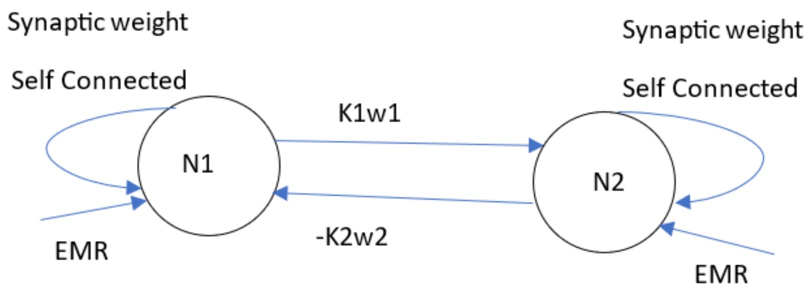

Fig. 1. a: two neurons with overlapping synapses, b: single EMR, c: double EMR

According to Fig. 1, the synapse interference between two neurons can be expressed as follows:

$$w_1 = a_1 - b_1 \tanh(x_1) + c_1 \tanh(x_4)$$
$$w_2 = a_2 - b_2 \tanh(x_4) + c_2 \tanh(x_3) \quad (3)$$

in which:

$$a_1 = \frac{R}{R_{a1}}, b_1 = \frac{R}{R_{b1}}, c_1 = \frac{gR^2}{R_{b1}\,R_{c1}}, a_2 = \frac{R}{R_{a2}}, b_2 = \frac{R}{R_{b2}}, c_2 = \frac{gR^2}{R_{b2}\,R_{c2}} \quad (4)$$

a1, b1, a2, b2 Memristor parameters and c1, c2 are interference power parameters.

2.2 HNN Model Based on Two Neurons

The formula of an HNN for two neurons is as follows:

$$c_1 \frac{dx_i}{dt} = -\frac{x_i}{R_i} \sum_{i=1}^{n} w_{ij} \tanh(x_i) + I_i \quad (5)$$

where ci, Ri, xi represents, membrane capacity, membrane resistance and voltage. and tanh(xi) is the activation function of the neuron, and W is the synapse weight between neurons i,j, and Ii is the bias current. In this research, the memristor model based on EMR simulation has been used as an external stimulus for two neurons with intermediate synapses, and the mathematical model features of the memristor model are as follows:

$$i = w(\varphi)v$$
$$\frac{d\varphi}{dt} = g(\varphi, v)$$
$$w(\varphi) = p(\alpha + \beta\varphi^2)$$
$$g(\varphi, v) = \mu v + \varepsilon\varphi \quad (6)$$

i is current, v is voltage, φ is magnetic flux and W(φ) is memory conductivity. $\alpha, \beta, \varphi, \varepsilon$ are the adjustable parameters of the EMR model In this article, the HNN model with two neurons and synapse weight values are set to appropriate weights, which are first checked without the intervention of EMR. In the following equation, a sinusoidal excitation is used for the memristor model:

$$v = A\sin(f * t)$$
$$I = p(\alpha + 3\beta\varphi^2)v$$
$$\frac{d\varphi}{dt} = \mu v \quad (7)$$

where A, F are the amplitude and frequency of the sinusoidal stimulus, respectively, when the parameters $\alpha = \beta = \mu = 1$, $\varphi = 2$ and A=1 are fixed and F is set to the values of 1, 3,9 and 12 respectively, in Fig. 2 it can be seen that the equation (7) Based on these values, it has three outputs of this type of memristor, each frequency forms a hysteresis loop and passes through the origin, and becomes linear as the output frequency increases.

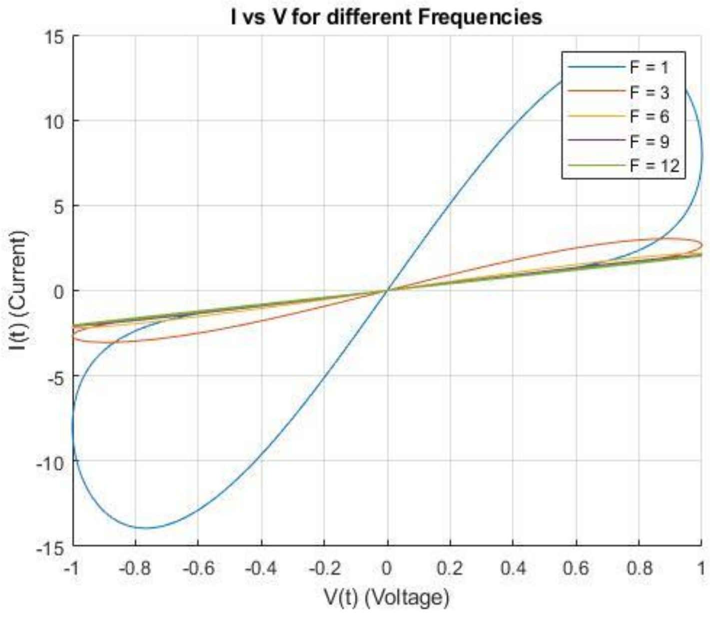

Fig. 2. Memristor model with fixed values of A=1,F=1;F=3;F=6;F=9;F=12, output of hysteresis loops

Using equation 5.6, HNN model with overlapping synapse and EMR bone according to Fig. 1, part a is as follows:

$$\begin{aligned}
\dot{x_1} &= -x_1 - 1.5\tanh(x_1) + \tanh(x_2) - 1.5\tanh(x_3) - 1.5\tanh(x_4) \\
\dot{x_2} &= -x_2 - 2.2\tanh(x_1) - .5\tanh(x_2) + \tanh(x_2) + 2.5\tanh(x_3) - 1.5\tanh(x_4) \\
\dot{x_3} &= -x_3 - .5\tanh(x_1) \\
\dot{x_4} &= -x_4 - \tanh(x_2)
\end{aligned} \tag{8}$$

x_i(i=1,2) and φ is the state variable of the system.

In the second case, using a single EMR according to Fig. 1, part b:

$$\begin{aligned}
&\dot{x_1} = -x_1 - 1.5\tanh(x_1) + \tanh(x_2) - 1.5\tanh(x_3) - 1.5\tanh(x_4) \\
&+\varphi(\alpha + 3\beta\varphi^2)x_1 \\
&\dot{x_2} = -x_2 - 2.2\tanh(x_1) - .5\tanh(x_2) + \tanh(x_2) + 2.5\tanh(x_3) - 1.5\tanh(x_4) \\
&\dot{x_3} = -x_3 - .5\tanh(x_1) + 1.4\tanh(x_2) + \tanh(x_3) + 1.5\tanh(x_4) \\
&\dot{x_4} = -x_4 + 5\tanh(x_1) - 1.5\tanh(x_2) - 2.5\tanh(x_3) + 3\tanh(x_4) \\
&\varphi = \mu\, x_1
\end{aligned} \tag{9}$$

In the third case, using two EMRs according to Fig. 1, part C:

$$\begin{aligned}
&\dot{x_1} = -x_1 - 1.5\tanh(x_1) + \tanh(x_2) - 1.5\tanh(x_3) - 1.5\tanh(x_4) \\
&+\varphi(\alpha + 3\beta\varphi^2)x_1 \\
&\dot{x_2} = -x_2 - 2.2\tanh(x_1) - .5\tanh(x_2) + \tanh(x_2) + 2.5\tanh(x_3) - 1.5\tanh(x_4) \\
&\dot{x_3} = -x_3 - .5\tanh(x_1) + 1.4\tanh(x_2) + \tanh(x_3) + 1.5\tanh(x_4) \\
&\dot{x_4} = -x_2 - 2.2\tanh(x_1) - .5\tanh(x_2) + \tanh(x_2) + 2.5\tanh(x_3) - 1.5\tanh(x_4) \\
&\varphi_1 = \mu_1\, x_1 \\
&\varphi_2 = \mu_2\, x_2
\end{aligned} \tag{10}$$

x_i(i=1,2) and φ_1, φ_2 is the state variable of the system.

2.3 Stability Analysis with Mathematical and Visual Model

To analyze the stability of all three cases, the first case of two neurons with overlapping synapses without EMR, the second case of two neurons with overlapping synapses and single EMR, the third case of two neurons with overlapping synapses and with two EMRs have been analyzed by mathematical and visual analysis methods for In the first case, we set the mathematical equation 8 equal to 0.

$$\begin{aligned}
0 &= -x_1 - 1.5\tanh(x_1) + \tanh(x_2) - 1.5\tanh(x_3) - 1.5\tanh(x_4) \\
0 &= -x_2 - 2.2\tanh(x_1) - .5\tanh(x_2) + \tanh(x_2) + 2.5\tanh(x_3) - 1.5\tanh(x_4) \\
0 &= -x_3 - .5\tanh(x_1) \\
0 &= -x_4 - \tanh(x_2)
\end{aligned} \tag{11}$$

From equation 11, the implied function of equation 12 can be obtained by placing $x_3 = .5\tanh(x_1)$ and $x_4 = \tanh(x_2)$ instead of x_1 and x instead of x_2 , y in equation 11, and based on this equation, the Fig. 3 equilibrium point for the first case is determined.

$$\begin{aligned}
H_{1(x,y)} &= -x - 1.5\tanh(x) + \tanh(y) - 1.5\tanh(.5\tanh(x) - 1.5\tanh(y)) \\
H_{2(x,y)} &= -y - 2.2\tanh(x) - .5\tanh(y) + \tanh(y) + 2.5\tanh(.5\tanh(y)) - 1.5\tanh(tanh(y))
\end{aligned} \tag{12}$$

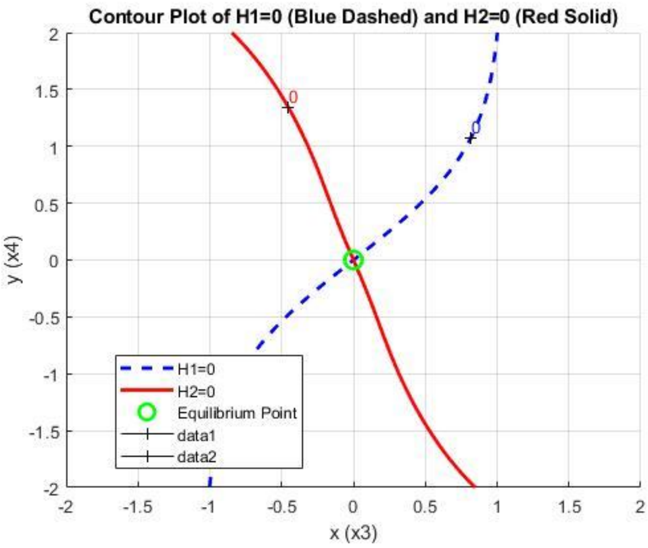

Fig. 3. Fixed point for the two-neuron case with synapse interference without ENR

For the second case, we set the mathematical equation 9 equal to 0.

$$\begin{aligned} 0 &= -x_1 - 1.5\tanh(x_1) + \tanh(x_2) - 1.5\tanh(x_3) - 1.5\tanh(x_4) + \varphi(\alpha + 3\beta\varphi^2)x_1 \\ 0 &= -x_2 - 2.2\tanh(x_1) - .5\tanh(x_2) + \tanh(x_2) + 2.5\tanh(x_3) - 1.5\tanh(x_4) \\ 0 &= -x_3 - .5\tanh(x_1) + 1.4\tanh(x_2) + \tanh(x_3) + 1.5\tanh(x_4) \\ 0 &= -x_4 + 5\tanh(x_1) - 1.5\tanh(x_2) - 2.5\tanh(x_3) + 3\tanh(x_4) \\ 0 &= \mu\, x_1 \end{aligned} \tag{13}$$

According to the section $0 = \mu\, x_1$ and because μ the intensity coefficient is related to EMR, so x_1 = 0 and its value is non-zero, so equation 12 becomes equation 13.

$$\begin{aligned} 0 &= -x_3 - 1.4\tanh(1.75\tanh(x_3) - 2.25\tanh(x_4)) + \tanh(x_3) + 1.5\tanh(x_4) \\ 0 &= -x_4 + 1.5\tanh(1.75\tanh(x_3) - 2.25\tanh(x_4)) - 2.5\tanh(x_3) + 3\tanh(x_4) \end{aligned} \tag{14}$$

From equation 13, by setting x_3 equal to x and x_4 equal to y, the implied function of equation 15 can be obtained, and based on this equation, Fig. 4 and the equilibrium point for the second case are determined.

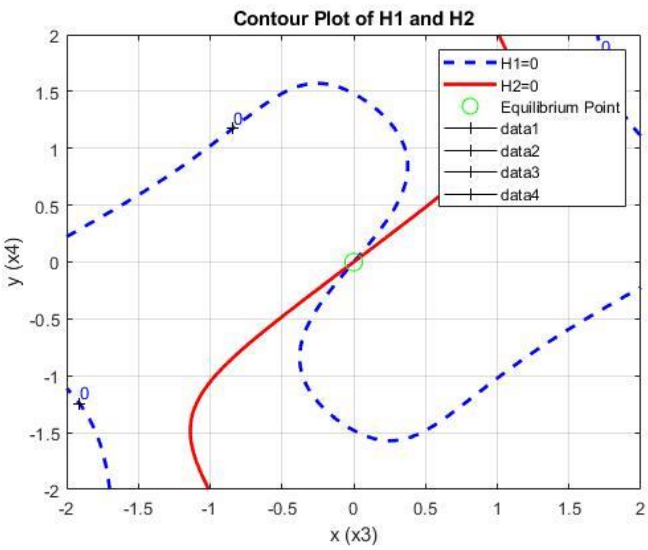

Fig. 4. Fixed point for two neurons with synapse interference and single EMR

$$H_{1(x,y)} = -x + 1.4\tanh(1.75\tanh(x)) - 2.25\tanh(y) + \tanh(x) + 1.5\tanh(y))$$
$$H_{2(x,y)} = -y - 1.5\tanh(1.75\tanh(x) - 2.25\tanh(y)) - 2.5\tanh(x) + 3\tanh(tanh(y)) \quad (15)$$

For the third case, we set the mathematical equation 10 equal to 0.

$$\begin{aligned}
0 &= -x_1 - 1.5\tanh(x_1) + \tanh(x_2) - 1.5\tanh(x_3) - 1.5\tanh(x_4) + \varphi(\alpha + 3\beta\varphi^2)x_1 \\
0 &= -x_2 - 2.2\tanh(x_1) - .5\tanh(x_2) + \tanh(x_2) + 2.5\tanh(x_3) - 1.5\tanh(x_4) \\
0 &= -x_3 - .5\tanh(x_1) + 1.4\tanh(x_2) + \tanh(x_3) + 1.5\tanh(x_4) \\
0 &= -x_2 - 2.2\tanh(x_1) - .5\tanh(x_2) + \tanh(x_2) + 2.5\tanh(x_3) - 1.5\tanh(x_4) \\
0 &= \mu_1 x_1 \\
0 &= \mu_2 x_2
\end{aligned} \quad (16)$$

According to the section $0 = \mu_1 x_1$ and $0 = \mu_2 x_2$, because μ_1 and $\mu_2$are intensity coefficients related to EMR, it is non-zero. Therefore, $x_1 = 0$ and $x_2 = 0$, so equation 16 becomes equation 17.

$$\begin{aligned}
0 &= -1.5\tanh(x_3) - 1.5\tanh(x_4) \\
0 &= -2.5\tanh(x_3) - 1.5\tanh(x_4) \\
0 &= -x_3 + \tanh(x_3) + 1.5\tanh(x_4) \\
0 &= -x_4 - 2.5\tanh(x_3) - 3\tanh(x_4)
\end{aligned} \quad (17)$$

From equation 17, by settingx_3 equal to x and $x_4$equal to y, the implicit function of equation 18 can be obtained, and based on this equation, Fig. 5 and the equilibrium point of the third case are determined.

$$\begin{aligned}
H_{1(x,y)} &= -1.5\tanh(x) - 1.5\tanh(y) \\
H_{2(x,y)} &= -2.5\tanh(x) - 1.5\tanh(y) \\
H_{3(x,y)} &= -x + \tanh(x) + 1.5\tanh(y) \\
H_{4(x,y)} &= -y - 2.5\tanh(x) - 3\tanh(y)
\end{aligned} \quad (18)$$

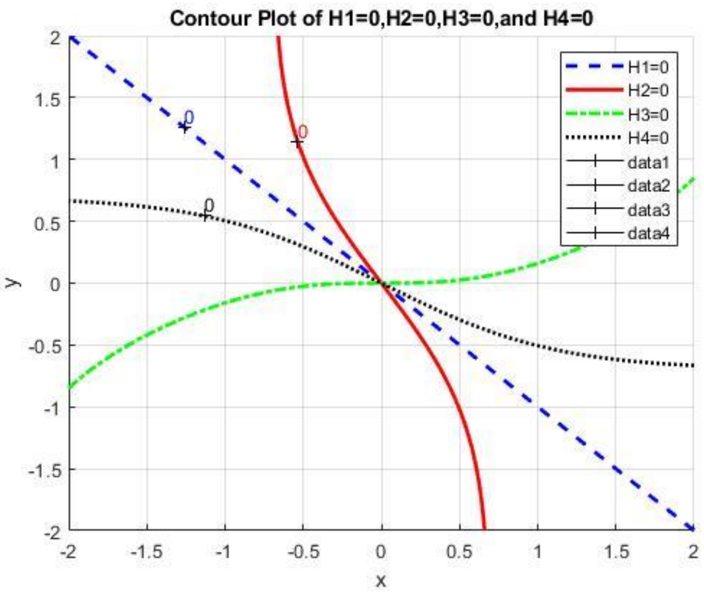

Fig. 5. Fixed point for two neurons with synapse interference and two EMRs

In Fig. 4, you can see that the system is at the equilibrium point when all four points $x_1, x_2, , x_3, x_4$ are equal to zero and constant, and according to equation 13, the value of μ_1 can have an arbitrary value, and there can be an infinite number of points, and the system is still in the state Equilibrium remains, i.e. (0,0,0,0, p), so p can change in the scope of its definition, which creates a one-dimensional path in a 5-dimensional space. In the nonlinear system, the equilibrium point is the point that does not change state in the system. In Fig. 5, the values of μ_1, μ_2 are arbitrary values, so they form a 2-dimensional space and a plane, and any point on this surface can be an equilibrium state in the 6-dimensional space, because μ_1, μ_2 can take different values, so there are many equilibrium states.

3. ANALYZING THE DYNAMIC BEHAVIOR OF HNN

3.1 Analyzing the Dynamic Behavior of HNN by Lyapunov Power

Lyapunov power is used to describe the chaotic behavior of nonlinear dynamic systems.In this section, the analysis of the dynamic behaviors of the HNN model without EMR in Fig. 6 and with a single EMR in Fig. 7 and with two EMRs in Fig. 8 with different values has been investigated.

The parameter a of the memristor model is considered as a variable parameter and has been checked with different values. The dynamic behavior of HNN with Lyapunov power shows that according to Fig. 6, the Lyapunov power of HNN in the state without EMR is -2.3 and Fig. 7 the Lyapunov power of HNN in the single EMR state is -2.8 and Fig. 8 shows that the Lyapunov power of HNN In the case of two EMRs at -3.1, the system has an obvious chaos phenomenon.

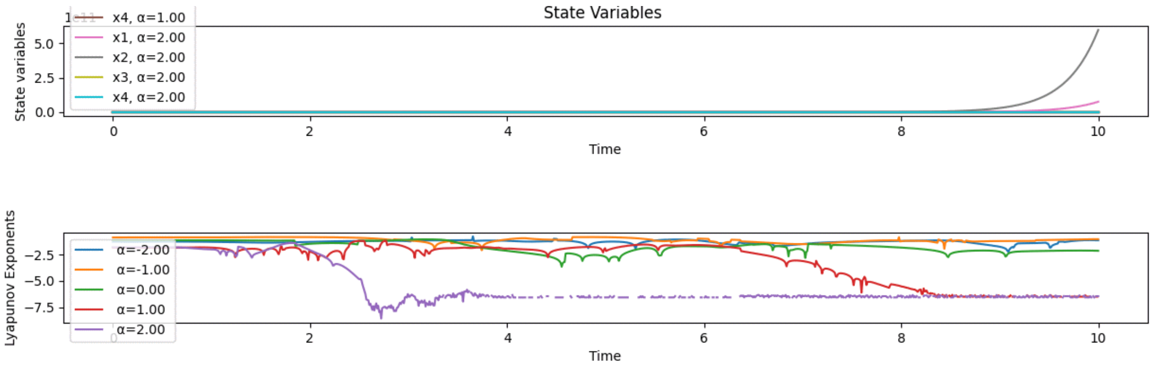

Fig. 6. Lyapunov power of HNN without EMR

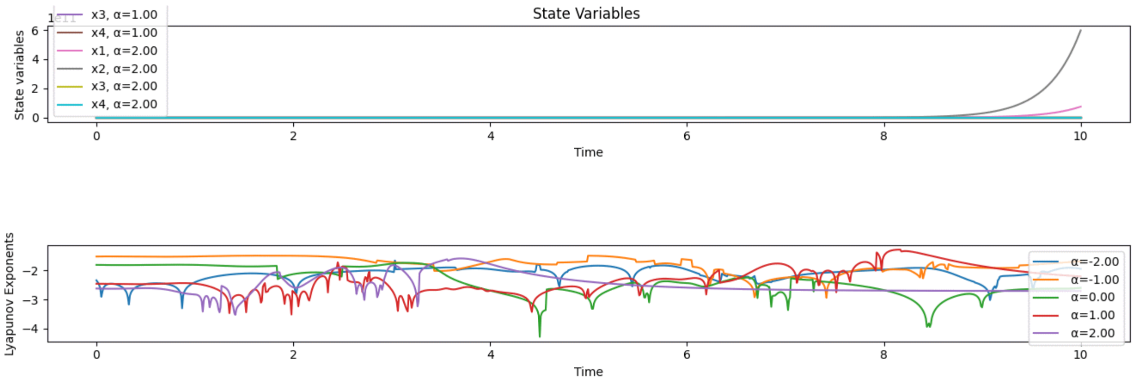

Fig. 7. Lyapunov power of HNN in single EMR mode

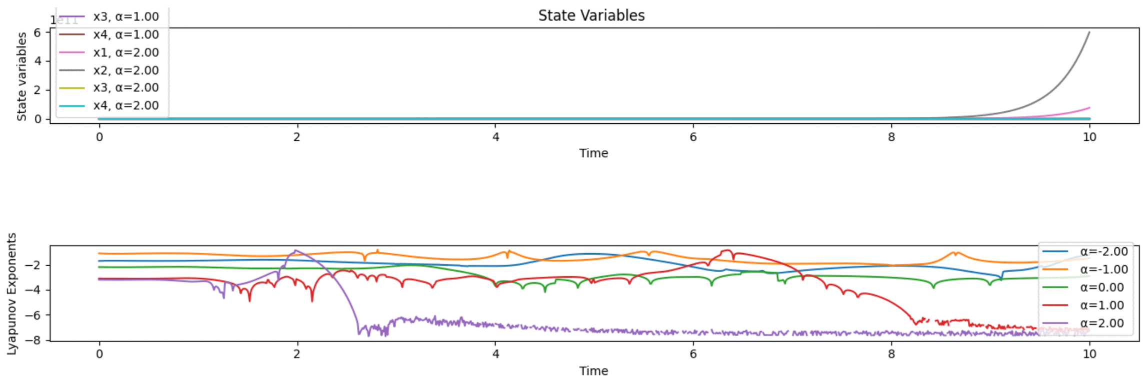

Fig. 8. Lyapunov power of HNN in the case of two EMRs

3.2 Analyzing the Dynamic Behavior of HNN by Phase Portrai

Fuzzy portrait is to record the path of the system with a shape that reveals the performance of the system. Then the fuzzy portrait is a graphical representation of the state trajectories of the dynamical system in the state space. Each point in this space represents the instantaneous state of the system, and the lines or curves represent the time evolution of these points. These portraits help us understand the behavior of the dynamical system, including fixed points, limit cycles, and attractors. And attraction is called a set of points in the state space towards which the dynamic system tends. In other words, if a system starts near this set of points, it will gravitate towards it. Attractors can take many forms such as Fixed Points, Limit Cycles, or more complex structures such as Strange Attractors. Transient chaos refers to a state in a dynamical system where the system is constrained for a limited period of time. It exhibits chaotic behavior, but eventually settles into an orderly behavior (usually gravity). This phenomenon is observed in many systems, where the system has an unpredictable and chaotic behavior at first, but over time it reaches a more stable pattern. Chaos in dynamic systems refers to a state in which the behavior of the system is very sensitive to It is the basic condition. Small changes in initial conditions can lead to large differences in system behavior. Chaotic systems have unpredictable and complex behavior, even if the governing equations are fully determinable. Strange gravity is a special type of gravity found in chaotic systems. Unlike simple attractions such as fixed points or limit cycles, these attractions have a complex and fractal structure. This means that they are infinitely detailed in dimensions, and the paths of the system around them can be very complex and unpredictable. In dynamic systems with fuzzy portraits, all these things can be understood with images, and in general, they help to understand the complex and unpredictable behavior of HNN dynamic systems. Chaos theory shows that even simple systems can have very complex behaviors that are sensitive to initial conditions. Dynamic behavior of the system for three states with initial values of $\alpha = 1, \beta = -1, \rho = 2, \mu_1 = \mu_2 = 1$ has been checked. Fig. 9 for the HNN mode with synapse interference without EMR, where the phase portrait represents the periodic mode.

Fig. 10 for the state of the neural network with synapse interference with single EMR, where the fuzzy portrait shows the state of transient chaos.

Fig. 11 for the state of the neural network with synapse interference with two EMRs, where the fuzzy portrait represents the state of chaos.

If we change the value of $\alpha = -1$ in Fig. 11 to the value of $\alpha = -1.4$, the chaotic state of the tidal system will become a transient chaotic state as shown in Fig. 12. Therefore, changing the initial value of the values directly affects the system state.

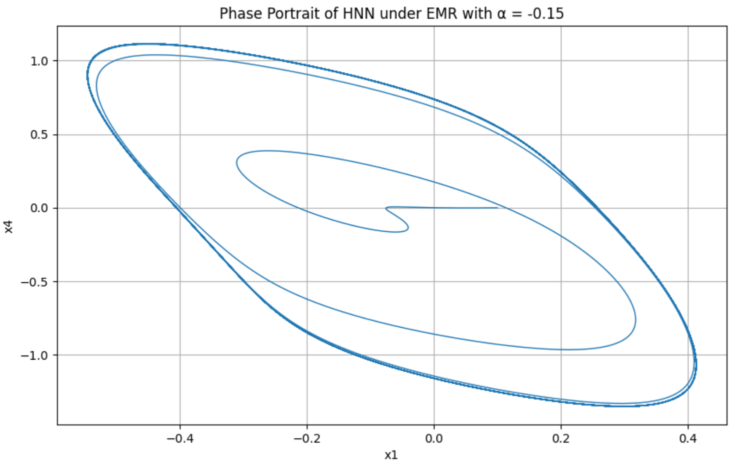

Fig. 9. HNN with synapse interference without EMR

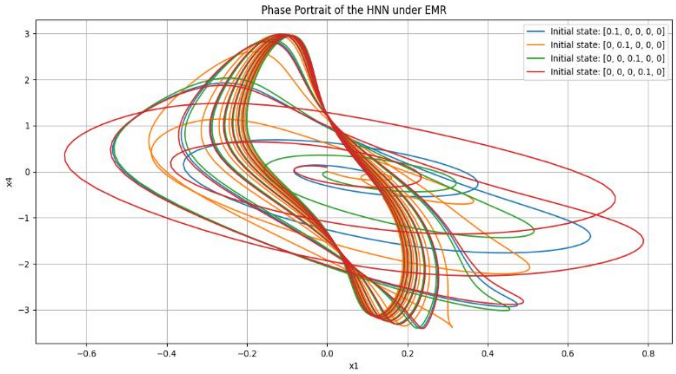

Fig. 10. Neural network with synapse interference with single EMR

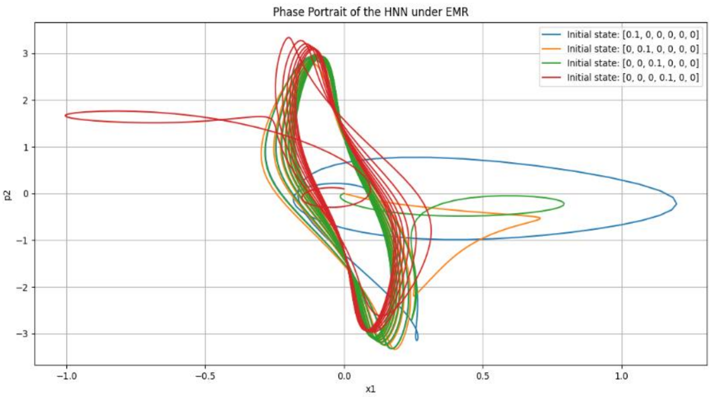

Fig. 11. Neural network with synapse interference with two EMRs

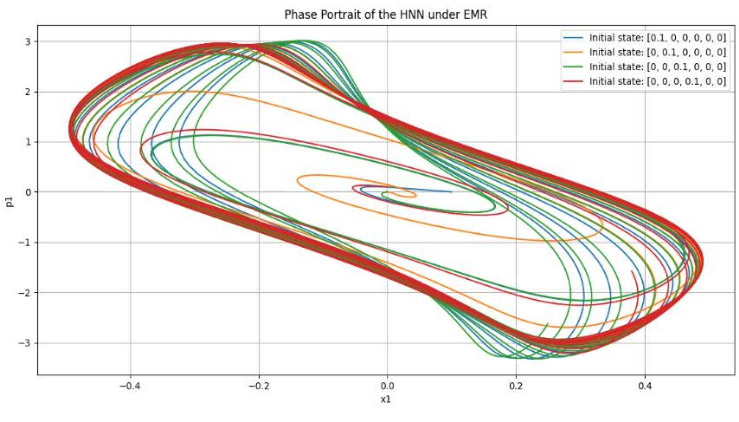

Fig. 12. Neural network with synapse interference and with two EMRs and $\alpha = -1.4$

4. CIRCUIT SIMULATION WITH PSPICE

To design the HNN circuit based on mathematical equations and based on two neurons, and without EMR in Fig. 13 and the EMR circuit itself is also seen in Fig. 15. The HNN circuit based on two neurons and overlapping synapses with single EMR is shown in Fig.16 and the HNN circuit based on two neurons and overlapping synapses with two EMRs is shown in Fig. 18.

4.1 Simulation of Neural Network Circuit with Synapse Interference without EMR with Pspice

It includes tanh circuit and synapse weight and the overall circuit is specified in diagram 13

All values and components of the circuit are specified in the figure. After designing the circuit and implementing the output of the circuit in Fig. 13, the output of this dynamic system is periodic. which you can see in diagram 14.

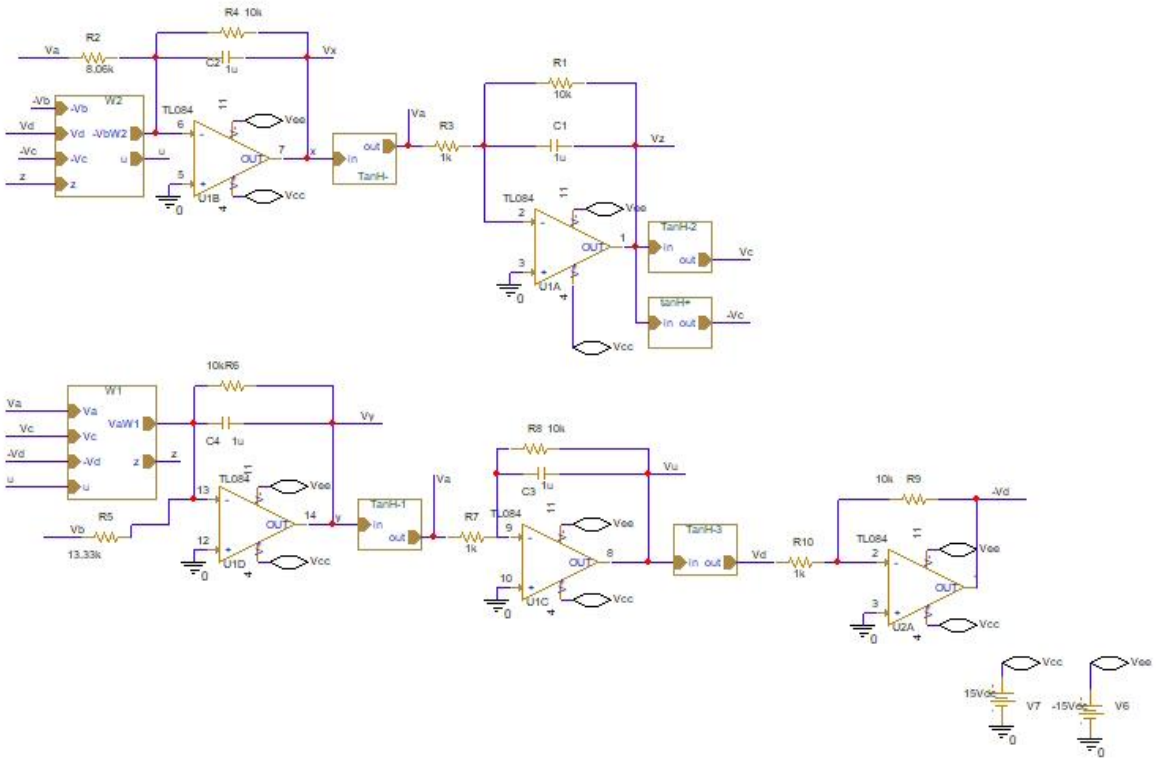

Fig. 13. Memristive HNN circuit with synaptic interference and no EMR

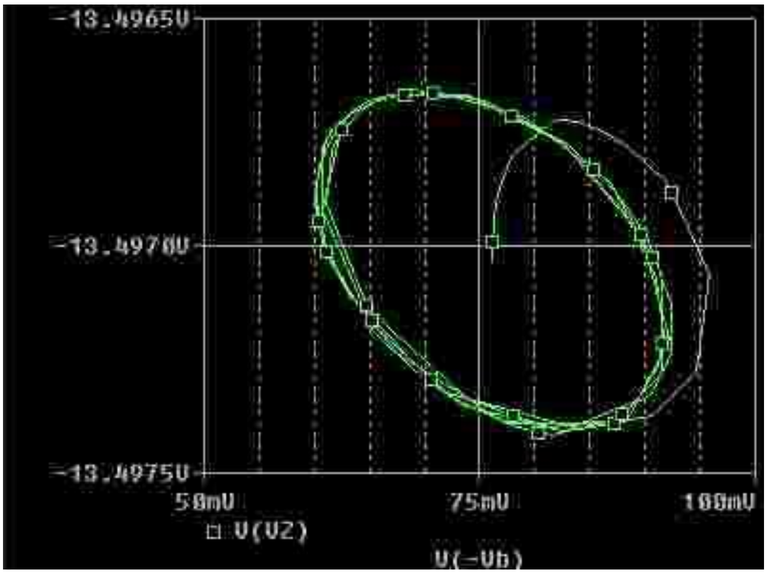

Fig. 14. HNN circuit with synapse interference without EMR

4.2 Simulating Neural Network Circuit with Synapse Interference with Single EMR with Pspice

The EMR circuit is shown in Fig. 15, and the HNN circuit with overlapping synapses and an EMR is designed in Fig. 16.

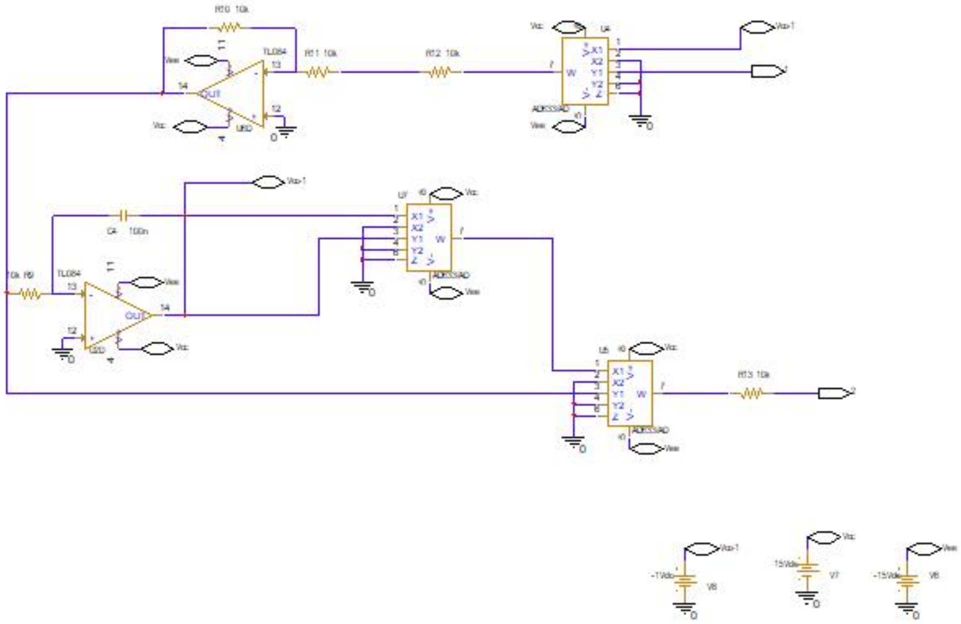

Fig 15. EMR circuit

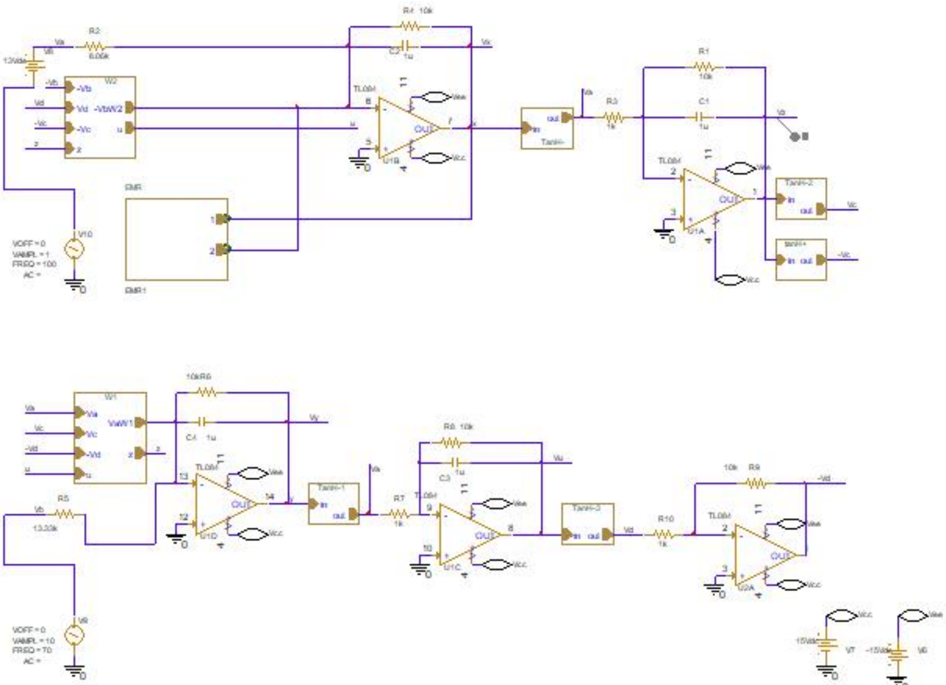

Fig. 16. HNN circuit with cross synapses and an EMR

After the execution of circuit 16, the output of circuit 17 is obtained, which produces a transient chaotic state.

4.3 Simulation of Neural Network Circuit with Synapse Interference with two EMRs with Pspice

It is the same as circuit 16, only the circuit has two EMRs, which is designed in Fig. 18.

The output of the circuit in Fig. 18 is checked in two states with frequency 100 in Fig. 19 and 130 in Fig. 20. In Fig. 19, the system has a chaotic state, but with the change of frequency in Fig. 20, the system turns into a transient state of chaos, which shows that the system has a slight change. It has different modes and is sensitive to initial conditions

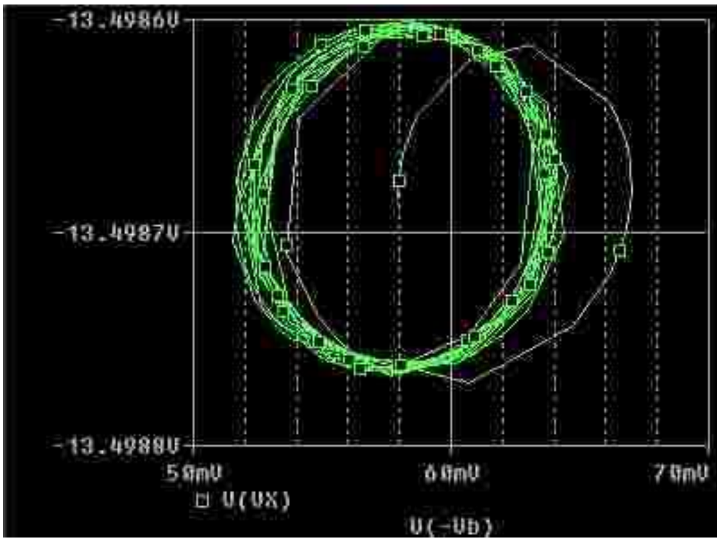

Fig 17. HNN circuit with synapse interference with single EMR

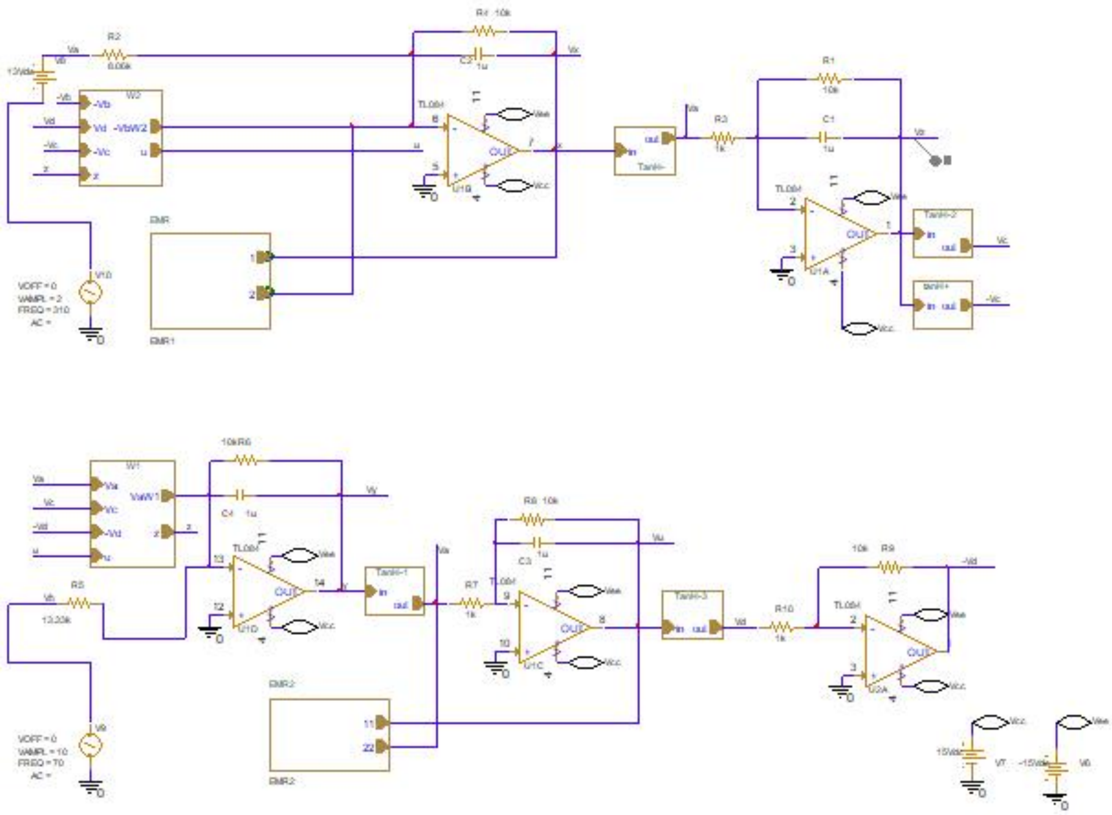

Fig. 18. HNN circuit with crossed synapses and two EMRs

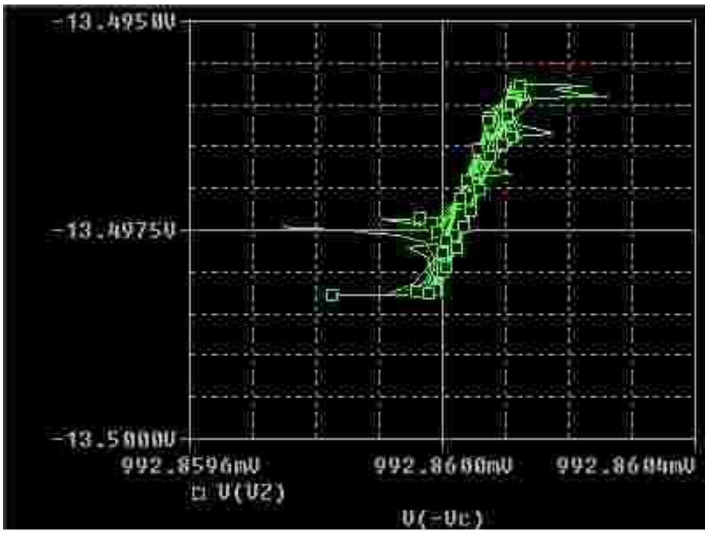

Fig 19. The output of the circuit in Fig. 18 with a frequency of 100

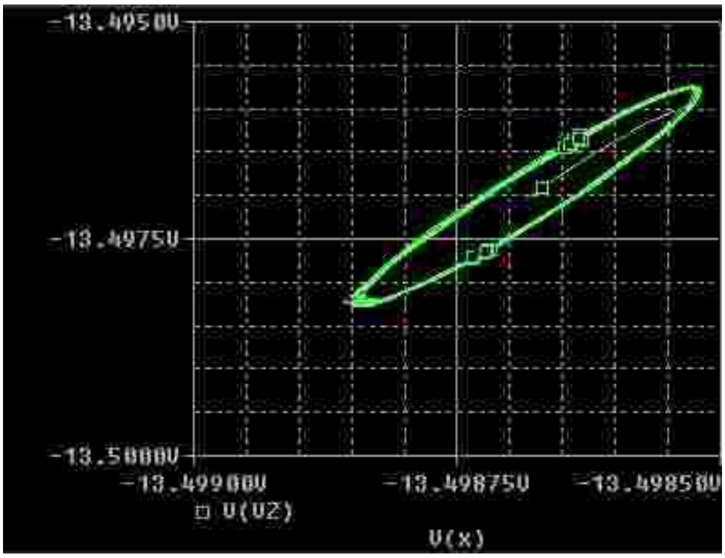

Fig. 20. The output of the circuit in Fig. 18 with a frequency of 130

5. CONCLUSION

In this research, the chaotic dynamics of HNN of two neurons with synapse interference were investigated for three body states of EMR, single EMR, and two EMRs. The second cases of single EMR affecting one neuron and the third case of double EMR affecting two neurons are presented respectively. Through the study, it was first found that chaotic phenomena can be observed by Lyapunov power. By examining the phase portraits for all three states of chaos and multi-period phenomena appeared, and the properties of dual EMR suppression in the chaos of the system are also changed by changing the initial values. The results show that the external stimulus represented by EMR can affect the inherently chaotic system. It can both have more complex dynamic behavior and suppress complex chaotic behavior by changing parameters. Finally, the feasibility of this theory is confirmed by circuit and pspice experiments, and the results of this study are used in the control of chaotic phenomena. The key results are:

1. **Observation of Chaotic Behavior**: The study successfully identified chaotic dynamics in the two-neuron memristive Hopfield Neural Network (HNN) when subjected to different scenarios of electromagnetic radiation (EMR), demonstrating that both single and dual EMR inputs can induce chaos in the system.

2. **Lyapunov Analysis**: The chaotic phenomena were quantified using Lyapunov exponents, confirming that the external influence of EMR leads to significant instability and complexity in the neural network's dynamics, indicating that the system exhibits sensitive dependence on initial conditions.
3. **Phase Portraits and Multi-Periodic Behaviors**: Phase portraits for each EMR scenario revealed the emergence of multi-periodic phenomena, showcasing rich and complex dynamic behaviors that vary with the presence and arrangement of EMR.
4. **Impact of Dual EMR**: The analysis highlighted that dual EMR inputs not only induce chaos but also modify the system's chaotic properties, with changes in initial conditions affecting the degree of chaos and system behavior.
5. **Dynamic Control through EMR**: The study demonstrated that EMR can be strategically used as an external stimulus to control the chaotic dynamics within the two-neuron network, allowing for both the enhancement of complex behaviors and suppression of chaotic patterns by adjusting input parameters.
6. **Verification with PSpice Simulations**: The theoretical findings were validated through circuit simulations using PSpice, confirming the practical feasibility of controlling chaotic behavior in neural networks with EMR manipulation.
7. **Potential Applications**: The results underscore potential applications in neuromorphic computing, control systems, and communication technologies, where modulation of chaotic dynamics could lead to improved stability and reliability in complex systems.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of this manuscript.

COMPETING INTERESTS

Author has declared that no competing interests exist.

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