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SIMULATION AND ELECTRONIC DESIGN OF A CHAOTIC 5D ARTIFICIAL NEURAL NETWORK

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Abstract. *This study investigates the complex dynamics of a five-dimensional artificial neural network (ANN) system with a hyperbolic tangent activation function. The objective is to analyze the chaotic behavior and validate multi-platform implementation of the proposed system. The methodology involves numerical simulations in MATLAB-Simulink and LabVIEW, followed by circuit design in Multisim for hardware feasibility verification. Through systematic parameter variation, the system exhibits rich dynamical regimes, including periodic oscillations and chaos. Lyapunov exponent analysis reveals a positive value ($LE_1 = 0.035$) and Kaplan-Yorke dimension $D_{KY} = 2.488$, confirming chaotic dynamics with fractional attractor geometry. Bifurcation diagrams demonstrate transitions between periodic and chaotic states as parameter b varies. The Multisim circuit simulation results demonstrate excellent agreement with MATLAB-Simulink and LabVIEW outputs, confirming the system's robustness and practical implementability across different platforms for potential applications in secure communications and cryptography.*

Keywords: artificial neural networks, chaos, MultiSim, electronic circuits

SYMULACJA I PROJEKTOWANIE ELEKTRONICZNE PIĘCIOWYMIAROWEJ CHAOTYCZNEJ SZTUCZNEJ SIECI NEURONOWEJ

Streszczenie. *W niniejszym badaniu analizowana jest złożona dynamika pięciowymiarowego systemu sztucznej sieci neuronowej (ANN) z hiperboliczną funkcją aktywacji tangens. Celem jest analiza chaotycznego zachowania i walidacja wieloplatformowej implementacji proponowanego systemu. Metodologia obejmuje symulacje numeryczne w MATLAB-Simulink i LabVIEW, a następnie projektowanie obwodów w Multisim w celu weryfikacji wykonalności sprzętowej. Dzięki systematycznej zmianie parametrów system wykazuje bogate reżimy dynamiczne, w tym oscylacje okresowe i chaos. Analiza wykładnika Lyapunowa ujawnia wartość dodatnią ($LE_1 = 0,035$) i wymiar Kaplana-Yorke'a $D_{KY} = 2,488$, potwierdzając chaotyczną dynamikę z frakcyjną geometrią atraktorową. Diagramy bifurkacji pokazują przejścia między stanami okresowymi i chaotycznymi w miarę zmiany parametru b. Wyniki symulacji obwodu Multisim wykazują doskonałą zgodność z wynikami MATLAB-Simulink i LabVIEW, potwierdzając niezawodność systemu i praktyczną możliwość wdrożenia na różnych platformach do potencjalnych zastosowań w bezpiecznej komunikacji i kryptografii.*

Słowa kluczowe: sztuczne sieci neuronowe, chaos, MultiSim, układy elektroniczne

Introduction

Chaotic systems, characterized by high sensitivity to initial conditions and complex, unpredictable behavior, have found widespread application in secure communications and cryptography. Systems that not only exhibit rich dynamics but are also suitable for efficient hardware implementation are of particular interest, as this is a key requirement for modern applications such as IoT devices and embedded security systems.

Current research in this field is advancing along several fronts: the search for new chaotic systems with unique properties, their verification through electronic circuits and FPGAs, and the development of efficient encryption algorithms based on them.

For instance, the works of Sambas et al. [6–7] actively investigate new jerk and hyperjerk systems. These studies demonstrate a complete cycle: from mathematical modeling and dynamics analysis (bifurcations, Lyapunov exponents) to implementation in Multisim and on FPGAs, followed by application to image encryption. One of these works even employs a Feed-Forward Neural Network (FFNN) model to approximate the chaotic system.

The study by Bonny et al. [1] directly aligns with our work, presenting a new 5D hyperchaotic system. The authors also conduct its analysis, circuit implementation in Multisim, and FPGA realization, setting a high standard for the validation of such models. Additionally, they use an LSTM network to predict the system's behavior, indicating a growing interest in the synergy between neural networks and chaos.

The work of Ponnambalam et al. [5] presents a complex encryption system based on a 3D hyperchaotic system, successfully implemented on an ESP8266 microcontroller. This highlights the trend towards creating lightweight and efficient solutions suitable for real-time operation.

Despite the significant progress illustrated above, most efforts focus on specially engineered jerk systems. Conversely, Artificial Neural Networks (ANNs), particularly Continuous-Time Recurrent Neural Networks (CTRNNs) [3], whose architecture inherently generates complex nonlinear dynamics, remain less explored as chaos generators for practical applications. ANNs offer a fundamentally different, biologically-inspired approach to generating complex signals, which could lead to systems with novel cryptographic properties.

This study investigates the complex dynamics of a five-dimensional artificial neural network system with a hyperbolic tangent activation function [3, 8, 9]. The primary objective of this work is to comprehensively analyze the chaotic behavior and to validate the multi-platform implementation of the proposed system. The methodology involves numerical simulations in MATLAB-Simulink and LabVIEW, followed by circuit design in Multisim to verify hardware feasibility.

1. Mathematical model of 5D system with ANN

In recent years, artificial neural networks have attracted increasing attention as effective instruments for solving complex problems, especially those related to the modelling of brain-like dynamic processes. Among these, continuous-time recurrent neural networks (CTRNNs) are of special interest due to their ability to represent time-dependent processes through systems of coupled ordinary differential equations incorporating nonlinear activation functions, such as the hyperbolic tangent [3]. The general form of the dynamical equations governing such a network is given by:

$$\frac{dx_i}{dt} = -b_i x_i + \tanh \sum_{j=1,\, j\neq i}^{N} w_{ij} x_j \qquad (1)$$

where x_i denotes the internal state of the i-th neuron, b_i is its decay rate (or inverse time constant), w_{ij} are the elements of the synaptic connection matrix, and N is the total number of neurons in the network.

Progress in electronic circuit design has opened new avenues for constructing hardware-based models of neural networks, which are increasingly important in both theoretical and applied research. Such physical implementations not only offer insight into the mechanisms underlying biological neural systems but also facilitate the exploration of novel architectures for artificial intelligence. In this context, Sprott proposed a minimal artificial neural network configuration that exhibits chaotic dynamics, described by a system of four coupled differential equations of the form [9]:

$$\begin{cases} \frac{dx_1}{dt} = \tanh(x_4 - x_2) - bx_1 \\ \frac{dx_2}{dt} = \tanh(x_1 + x_4) - bx_2 \\ \frac{dx_3}{dt} = \tanh(x_1 + x_2 - x_4) - bx_3 \\ \frac{dx_4}{dt} = \tanh(x_3 - x_2) - bx_4 \end{cases} \quad (2)$$

As demonstrated by Sprott [6], variation of the parameter b in system (2) leads to qualitative changes in the dynamics, ranging from regular and quasiperiodic to chaotic behavior. The nonlinearity introduced by the hyperbolic tangent function, (tanh), which belongs to the class of sigmoid functions, imposes output saturation within finite bounds. This prevents divergence and ensures physically meaningful system behavior.

For the parameter value $b = 0.043$ and initial conditions $(x_1(0), x_2(0), x_3(0), x_4(0)) = (1.2, 0.4, 1.2, -1)$, the system exhibits a chaotic attractor. In the same work [6], the Lyapunov exponents $(LE_i, i = 1,2,3,4)$ and the corresponding Kaplan-Yorke dimension D_{KY} were also computed, confirming the presence of chaos, as follows:

$$LE_i = (0.03164, 0, -0.07313, -0.13051), \quad D_{KY} = 2.43263 \quad (3)$$

Building upon previous studies of low-dimensional neural dynamics, Samuilik et al. [8] advanced the analysis by introducing higher-dimensional artificial neural network (ANN) models. In particular, they proposed a five-dimensional (5D) system that generalizes the original four-dimensional structure while preserving the essential features of nonlinear recurrent interactions. The governing equations of the 5D ANN model are given by:

$$\begin{cases} \frac{dx_1}{dt} = \tanh(x_4 - x_2) - bx_1 \\ \frac{dx_2}{dt} = \tanh(x_1 + x_4) - bx_2 \\ \frac{dx_3}{dt} = \tanh(x_1 + x_2 - x_4) - bx_3 \\ \frac{dx_4}{dt} = \tanh(x_3 - x_2) - bx_4 \\ \frac{dx_5}{dt} = \tanh(x_1 + x_4 - x_5) - bx_5 \end{cases} \quad (4)$$

with initial conditions

$$x_1(0) = 1.2,\ x_2(0) = 0.4,\ x_3(0) = 1.2,\ x_4(0) = -1,\ x_5(0) = -1 \quad (5)$$

2. Dynamical analysis

System (4) was solved in the Mathematica environment using the following initial conditions (5). It was established [8] that for $b = 0.1$, system (4) exhibits periodic solutions (a limit cycle), characterized by the Lyapunov exponent signature $(0,-,-,-,-)$. In contrast, for $b = 0.043$ (or $b = 0.045$), the system displays chaotic behavior, as indicated by the Lyapunov exponent signature $(+,0,-,-,-)$ (see Fig. 1).

Fig. 2 illustrates the trajectories of two distinct attractors in system (4) obtained with the same parameter $b = 0.045$ but different initial conditions, thereby demonstrating the multistability exhibited by the chaotic system (4).

It should be noted that stable limit cycles in neural networks correspond to rhythmic brain activity, specifically oscillations that play a key role in cognitive processes such as attention, memory, and sensorimotor integration. Chaotic dynamics, in turn, is associated with the computational flexibility of neural systems and their ability to rapidly switch between different functional states. Recent studies show that the brain often operates in a metastable regime at the edge of order and chaos, which optimizes information processing. In the context of our model, transitions between regular and chaotic dynamics with changes in parameter b can be considered as a simplified model of switching between different functional regimes of the brain.

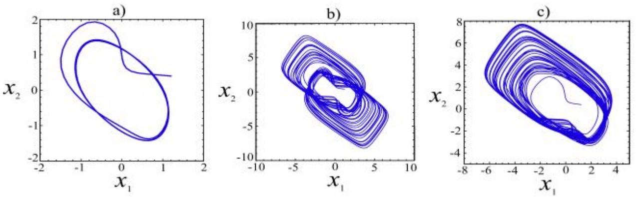

Fig. 1. Phase portraits of attractors in the x_1x_2 plane of system (4) for values of the parameter b equal: a) 0.15; b) 0.043; c) 0.045

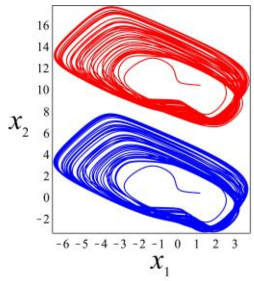

Fig. 2. Plots of two chaotic attractors in the x_1 x_2 plane of system (4) for different initial conditions: blue (1.2, 0.4, 1.2, -1, -1) *and red* (1.21, 0.41, 1.21, -1.01, -1.01) *trajectories. For clarity of visualization, the red attractor is shifted by +10 units along the x_2-axis*

We derive a condition under which the system (4) is dissipative:

$$\frac{\partial \dot{x}_1}{\partial x_1} + \frac{\partial \dot{x}_2}{\partial x_2} + \frac{\partial \dot{x}_3}{\partial x_3} + \frac{\partial \dot{x}_4}{\partial x_4} + \frac{\partial \dot{x}_5}{\partial x_5} = -5b - 1 + \tanh(x_1 + x_4 - x_5)^2 < 0$$

or

$$5b + 1 > (\tanh(x_1 + x_4 - x_5))^2 \quad (6)$$

Given that the hyperbolic tangent function is strictly bounded within the interval $[-1,1]$, it follows that system (4) is dissipative for any $b > 0$, as the nonlinearity cannot lead to unbounded growth. By setting the time derivatives in system (4) to zero, one finds that the system admits a unique equilibrium point at $E(0,0,0,0,0)$. To gain deeper insight into the system's dynamical behavior, the full Lyapunov spectrum was computed using the Benettin-Wolf algorithm with Gram-Schmidt orthonormalization.

To validate this methodology in Mathematica, we calculated all Lyapunov exponents for the Sprott system (2) with initial conditions $(x_1(0), x_2(0), x_3(0), x_4(0)) = (1.2, 0.4, 1.2, -1)$ in the following form:

$$LE_i = (0.035, 0, -0.085, -0.127) \quad (7)$$

A comparison between expressions (3) and (7) demonstrates good agreement with the results of Sprott [9]. Using this approach, we calculated all Lyapunov exponents and the Kaplan-Yorke dimension for system (4) with initial conditions (5) at $b = 0.043$ in the following form:

$$LE_i = (0.035, 0, -0.085, -0.127, -0.697),\ D_{KY} = 2.488 \quad (8)$$

Interestingly, the Kaplan-Yorke dimension computed for $b = 0.043$ exceeds that for $b = 0.045$, namely, $D_{KY}|_{b=0.043} > D_{KY}|_{b=0.045} = 2.386$ indicating a more complex underlying attractor despite the smaller parameter value. To investigate the local stability of the equilibrium point $E(0,0,0,0,0)$, we derived the characteristic equation of system (3) for $b = 0.043$. The resulting eigenvalue spectrum $\lambda_{(1,2,3,4,5)}$ consists of one negative real root and a pair of complex-conjugate roots, one of which possesses a positive real part:

$$\lambda_1 = -1.043,\ \lambda_{2,3} = -0.246 \pm i1.664,\ \lambda_{4,5} = 0.160 \pm i0.560$$

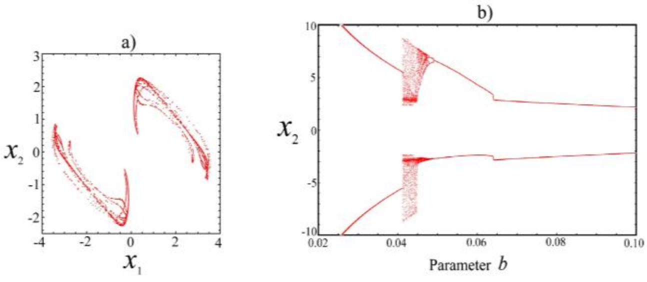

Fig. 3. a) Poincare section in the x_1x_2 – plane for (4) with b = 0.043 and x_4 = 0; b) bifurcation plot of x_2 component for (4) as b increases

This spectral configuration identifies the equilibrium as a saddle-focus, confirming its linear instability. Such instability is a hallmark of self-excited chaotic attractors, wherein the system trajectories emerge from the vicinity of the equilibrium before evolving into a bounded, chaotic regime. The corresponding chaotic attractor is depicted in Fig. 1a, while its Poincaré sections in the x_1x_2-plane for $x_4 = 0$ are shown in Fig. 3a, revealing a complex internal structure. To provide a broader picture of the system's response to parameter variation, bifurcation diagrams were constructed as functions of the control parameter b (see Fig. 3b). These diagrams clearly reveal the alternation between periodic, quasi-periodic, and chaotic regimes of the five-dimensional neural model.

3. Computer modelling and electronic circuit design

In this section, we use computer simulations to analyse the dynamics of a five-dimensional (5D) artificial neural network (ANN) chaotic system. Simulations are conducted in Simulink and LabVIEW, both visual design environments for modelling chaotic oscillators. Additionally, the 5D ANN chaotic system is successfully implemented in the Multisim environment, confirming its feasibility for hardware realization.

3.1. MATLAB-Simulink model

To perform numerical simulations of system (4) for the five-dimensional (5D) artificial neural network (ANN) system, we set the simulation time to t = 2000 s in MATLAB-Simulink. Simulink, integrated within MATLAB, provides a graphical user interface (GUI) and an extensive library for modelling and simulating various systems. Known for its intuitive design, it facilitates the analysis and control of analog, digital, and mixed systems while ensuring seamless integration of input and output signals with the MATLAB environment [4]. Using Simulink blocks, as shown in Fig. 4, we constructed a simulation model of system (4), incorporating the hyperbolic tangent activation function. The model consists of ten adder and subtractor blocks, five hyperbolic tangent function blocks, five gain blocks, and five integrator blocks from the Simulink math library. The gain blocks store the fixed parameter b values of system (4).

The simulation results, presented in Fig. 5, display two-dimensional phase portraits of strange chaotic attractors. These phase portraits exhibit strong similarity to those obtained using the Mathematica environment (see Fig. 1b). In MATLAB-Simulink, we employed the ode45 solver with variable step size (maximum 0.01), relative tolerance of 1e-6, and absolute tolerance of 1e-8.

3.2. LabVIEW model

In various engineering applications, LabVIEW is widely used alongside MATLAB-Simulink as a visual development environment. Fig. 6 presents a block diagram of the five-dimensional (5D) artificial neural network (ANN) chaotic system described by system (4). Our model utilizes the Control & Simulation and Formula Node toolboxes. The Formula Node is employed to define the right-hand sides of system (4) using the C programming language. The system equations are numerically solved using the Euler method, whose computational simplicity makes it well-suited for microcontroller programming. By replacing function blocks with a Formula Node, the block diagram is significantly simplified. Time derivative integration is performed using Integrator blocks from the Continuous palette.

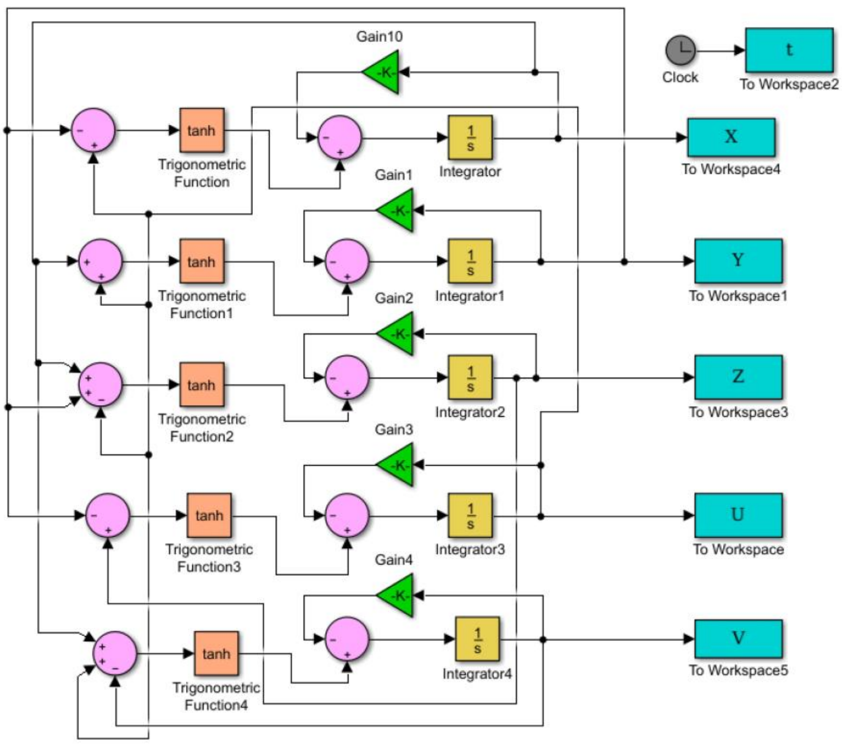

Fig. 4. MATLAB-Simulink model for system (4). Here the state variables X, Y, Z, U, V correspond to x_1, x_2, x_3, x_4, x_5 from system (4), respectively

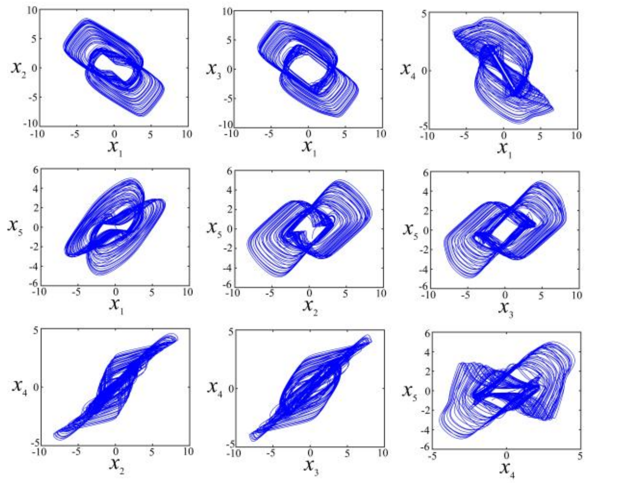

Fig. 5. Phase portraits of chaotic attractors obtained in the MATLAB-Simulink model

Fig. 7 displays the software interface illustrating the chaotic solutions of system (4) within the LabVIEW model. The simulation results are presented as phase portraits on the planes: x_1x_2, x_1x_3, x_1x_4, x_1x_5, x_2x_5, x_3x_5, x_2x_4, x_3x_4, x_4x_5, using the initial conditions (5). A comparison of the phase portraits in Fig. 4 and Fig. 7 demonstrates a strong similarity between the chaotic system simulations in MATLAB-Simulink and LabVIEW, confirming the consistency of the results across both platforms. In LabVIEW, the Euler method with a fixed step size of 0.001 was used. The LabVIEW-simulated time series of x_1, x_2, x_3, x_4, x_5 exhibit an aperiodic structure, a key characteristic of chaotic systems. As shown in Fig. 8, the dynamic variables x_i remain within the operational amplifiers' power supply limits (15 V), ensuring stable and reliable circuit operation.

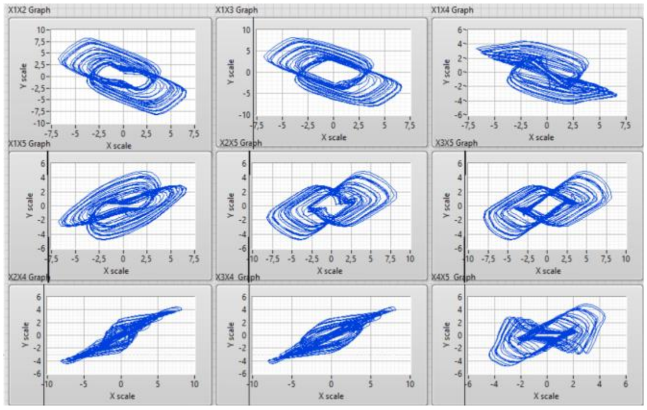

Fig. 7. Phase portraits in various planes obtained in LabVIEW. Here, the symbols X1, X2, etc., correspond to x_1, x_2, etc., from system (4)

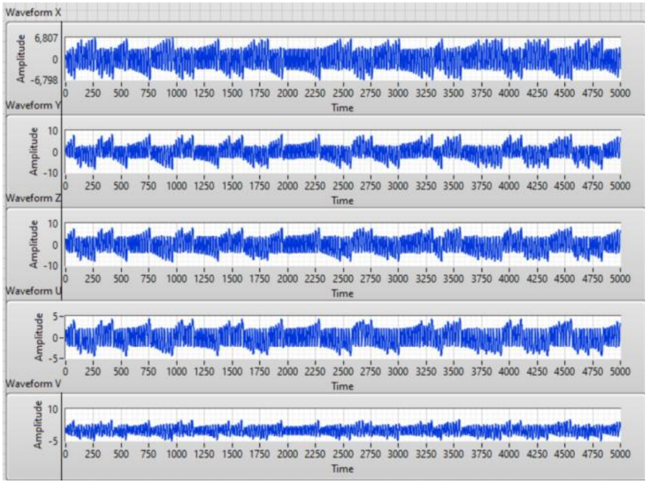

Fig. 8. Temporal diagrams of the different coordinates simulated in LabVIEW

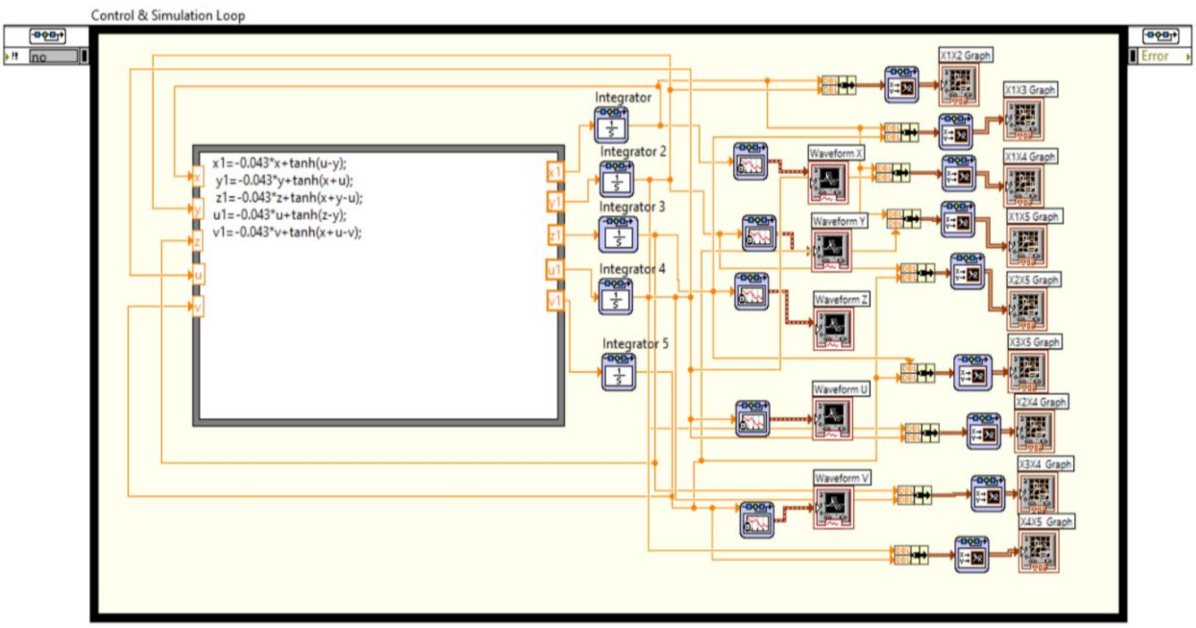

Fig. 6. Block diagram of the system (4) in LabVIEW

2.3. Electronic circuit implementation

The analog implementation of neurons and neural networks offers significant potential for artificial intelligence applications. In this section, we design an electronic circuit to realize the five-dimensional (5D) artificial neural network (ANN). The design leverages operational amplifiers and established electronic circuits to implement the hyperbolic tangent function [2]. The electronic circuit is assembled from ordinary components (resistors, capacitors, multipliers, diodes, and operational amplifiers) available in abundance in the Multisim environment library. In this implementation, the state variables of the dynamic system (4) are represented as electrical signals, corresponding to the instantaneous voltage values across capacitors C_1, C_2, C_3, C_4, C_5 denoted as $u_1(\tau), u_2(\tau), u_3(\tau), u_4(\tau), u_5(\tau)$.

Then, in accordance with Kirchhoff's laws for electrical circuits, we can write the electrical analogue of the system (4) as

$$\begin{aligned}
C_1\frac{du_1}{d\tau} &= -\frac{u_1}{R_1}+\frac{1}{R_2}\tanh(u_4-u_2)\\
C_2\frac{du_2}{d\tau} &= -\frac{u_2}{R_3}+\frac{1}{R_4}\tanh(u_1+u_4)\\
C_3\frac{du_3}{d\tau} &= -\frac{u_3}{R_5}+\frac{1}{R_6}\tanh(u_1+u_2-u_4)\\
C_4\frac{du_4}{d\tau} &= -\frac{u_4}{R_7}+\frac{1}{R_8}\tanh(u_3-u_2)\\
C_5\frac{du_5}{d\tau} &= -\frac{u_5}{R_9}+\frac{1}{R_{10}}\tanh(u_1+u_4-u_5)
\end{aligned} \tag{9}$$

where R_i represent resistors, C_i represent capacitors, and $\tau = t_0 t$. We normalize the resistor as $R_0 = 100$ kΩ and the capacitor as $C_0 = 0.15$ nF, giving a time constant of $t_0 = R_0 C_0 = 1.5\cdot 10^{-5}$ s. The state variables of the system (9) are rescaled as follows:

$$u_1 = U_0 x_1, u_2 = U_0 x_2, u_3 = U_0 x_3, u_4 = U_0 \tilde{x}_4, u_5 = U_0 x_5 \tag{10}$$

We are introducing $K = U_0 K'$, where K is a scaling coefficient for the multiplier. Here, $\tilde{x}_1, \tilde{x}_2, \tilde{x}_3, \tilde{x}_4, \tilde{x}_5$ are dimensionless variables for which equations (9) take a form similar to system (4). U_0 is a constant value that has the dimension of normalizing voltage.

By substituting R_0, $C_1 = C_2 = C_3 = C_4 = C_5 = C_0$ and $K' = 10$ into system (9) and comparing the numerical values of the output voltages in (9) and (4) for the parameter value $b = 0.043$, we determine the values of the electronic circuit resistors as follows:

$$R_{(1,3,5,7,9)} = 2.326\ \text{M}\Omega,\ R_{(2,4,6,8,10)} = 100\ \text{k}\Omega$$

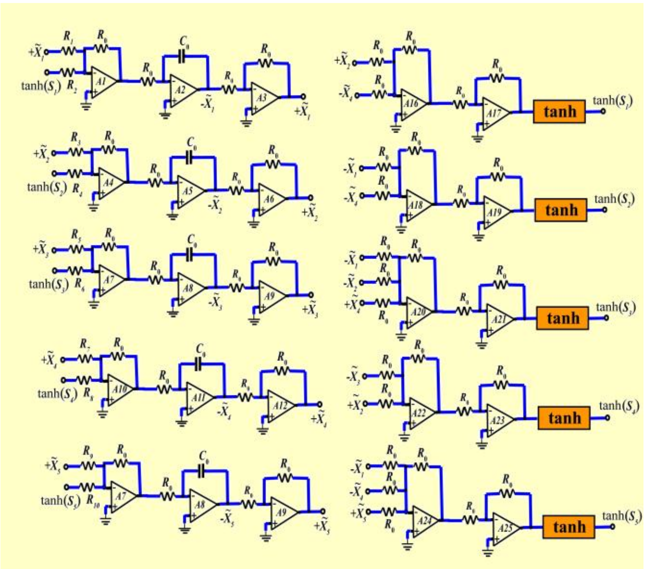

Fig. 9. Circuit modules implemented based on a system of equations (9)

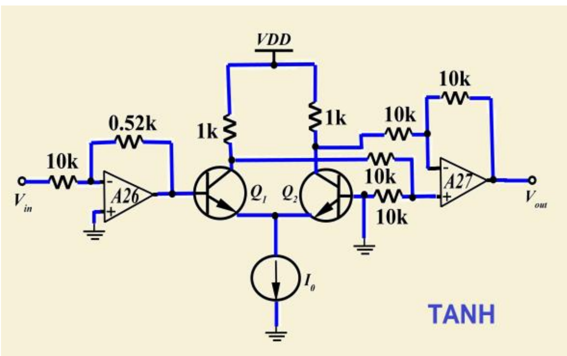

Fig. 10. Circuit scheme for realization of hyperbolic tangent function

Fig. 9 illustrates the analog circuit modules corresponding to the equations in system (4). These circuits are built using standard electronic components, including resistors (R), capacitors (C), operational amplifiers (A1-A27, TL084ACN), and a supply voltage of ±15 V. Fig. 10 presents the electronic circuits used to implement the hyperbolic tangent function [2]. As shown in Fig. 10, the equivalent circuit for the hyperbolic tangent function consists of two MPS2222 transistors (Q1 and Q2), two TL084ACN operational amplifiers, a current source $I_0 = 1.1$ mA, and several resistors. The simulation results of the circuit model are shown in Fig. 11. A comparison reveals that the outputs from Multisim closely align with those obtained from MATLAB-Simulink (Fig. 5) and LabVIEW (Fig. 7), confirming the consistency of the system's chaotic behavior across different simulation environments.

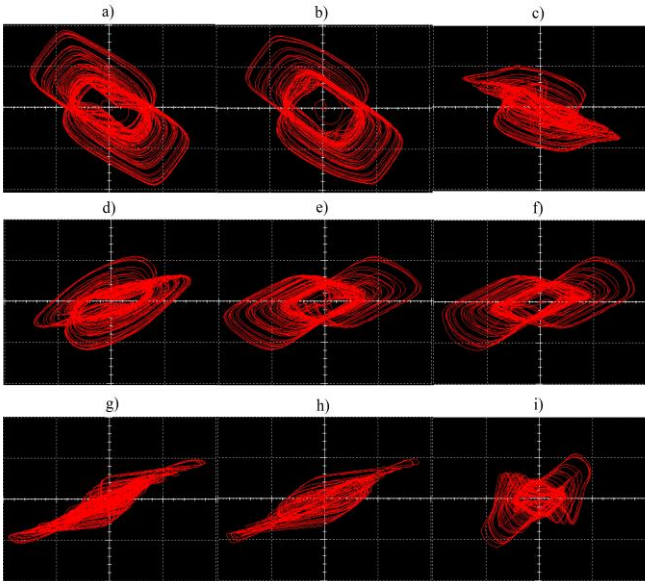

Fig. 11. Attractors of system (6) derived by Multisim oscilloscope

4. Conclusion

In this paper, we analyzed the dynamics of a five-dimensional (5D) artificial neural network (ANN) chaotic system based on the hyperbolic tangent sigmoidal function. We investigated key properties, including bifurcation behavior, Lyapunov exponents, and the Kaplan-Yorke dimension, alongside a detailed examination of phase portraits. Numerical simulations were conducted using Matlab-Simulink and LabVIEW to explore the system's nonlinear dynamics. Phase portraits obtained from these simulations confirm that the system exhibits complex chaotic oscillations at specific control parameter values. Furthermore, we designed an electronic circuit to implement a chaos generator based on the 5D ANN system and validated its performance through Multisim simulations.

The proposed 5D chaotic system offers unique advantages for high-security cryptographic applications, where the five-dimensional phase space provides superior complexity compared to lower-dimensional systems. Additionally, the multiple coexisting attractors can serve as memory states in associative memory and pattern recognition tasks. Future work will focus on the hardware realization of this system and its potential applications.

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