https://doi.org/10.5755/j02.eie.38220 ELEKTRONIKA IR ELEKTROTECHNIKA, ISSN 1392-1215, VOL. 30, NO. 4, 2024

Logical Resonance in Izhikevich Neuron

Vedat Burak Yucedag[1], Ilker Dalkiran[1,*], Arash Ahmadi[2]
[1]*Department of Electrical and Electronics Engineering, Erciyes University, Ahmet El Biruni Street, 38030, Melikgazi, Kayseri, Turkiye*
[2]*Department of Electronics Engineering, Carleton University, 1125 Colonel by Drive, K1S 5B6, Ottawa, ON, Canada*
*vedatburakyucedag@erciyes.edu.tr; *ilkerd@erciyes.edu.tr; aahmadi@doe.carleton.ca*

***Abstract*—This paper proposes a new logic element model based on an Izhikevich (IZ) neuron and neural system that emulates two- and three-state logic behaviours. In a noise-free environment, with a periodic current of suitable amplitude and frequency, the IZ system is capable of performing logical AND and OR operations. Initially, a single IZ neuron demonstrates membrane dynamics in response to an input signal generated by combining two-state logic currents below the threshold. Subsequently, an IZ neural system model is introduced to enhance the reliability and resilience of the system. This model is characterised by electrical coupling with fast conduction and chemical coupling with a more adaptable structure. Each logic input independently influences each neuron within the system. Additionally, it has been observed that the reliability of the logic element is influenced by changes in synaptic strength, with a neural system lacking sufficient synaptic strength failing to generate logical output. Furthermore, the system displays a three-state logic behaviour under suitable forcing periodicity, thus enhancing the power efficiency of the logic element. The proposed IZ neuron and neural system are expected to significantly impact the development of brain-inspired logic elements.**

***Index Terms*—Izhikevich; Logical stochastic resonance; Logical vibrational resonance; Electrical-chemical coupling.**

I. INTRODUCTION

Noise is a critical factor that must be considered in the design of any implementation platform [1]. The impact of noise becomes more visible as the dimensions of the design and the power decrease [2]. Understanding the interplay between device nonlinearity and the noise floor is crucial in design and implementation platforms, as noise, being unavoidable, can detrimentally affect performance [3]. However, recent studies indicate that noise is not always harmful and can, in fact, be beneficial in some nonlinear systems [4]–[8]. In this context, noise can induce increased temporal regularity, a phenomenon known as stochastic resonance (SR) [9]. Stochastic resonance studies have unveiled that nonlinear system responses are amplified through a periodic force, akin to the effects of noise. This phenomenon, dubbed vibrational resonance, improves the processing capacity of the subthreshold signal by using a periodic signal [10]. The periodic force reduces the switching time to achieve a faster response and broadens the optimal noise power range [11].

Although traditional logic gate design relies on deterministic input signals, the introduction of logical stochastic resonance (LSR) allows nonlinear systems to utilise noise to implement logic functions [12]. The inherent interplay between the noise floor and nonlinearity can be used to obtain highly reliable logic gate outputs from a bistable system within an optimal window of moderate noise [13]. This approach has important implications for the design of integrated systems, neural networks, and analogue circuits [14], [15]. With the increasing miniaturisation of electronic devices, noise has become more critical and has become a frequently researched topic [16]–[18]. Typically, elevated noise fluctuations have the potential to undermine the reliability of logic devices, resulting in a diminished computational performance [19]. Variations in temperature within the environment and changes in device workload can lead to fluctuations in noise intensity [20]. Furthermore, the use of periodic signals as a driving force, rather than noise, is more favourable to the regulation of logic operations [21]. Practically, a wider range of optimal parameters and a shorter switching time are anticipated to improve the robustness and response speed of the system [22]. This phenomenon is called "logical vibrational resonance" (LVR) [23].

Compared to traditional computers, brain-inspired neuromorphic devices are known to have the potential for high computing capacity and better energy efficiency [24]–[27]. The significance of neuromorphic devices has grown with the surge in big data analytics and artificial intelligence research [27]. Novel approaches are driving computational capabilities to higher levels at reduced costs [24]. Recently, a new generation of neuron-inspired logic gates, based on Hodgkin-Huxley (HH) and FitzHugh-Nagumo (FHN) neuron models, have been introduced [20], [22], [28]–[31]. However, these models come with certain drawbacks:

1. Logic inputs summed at subthreshold levels are fed to a single neuron, and the cumulative inputs can potentially drive the neuron above the desired superthreshold level, leading to unintended firing. This issue reduces the reliability of the logic gate [29], [30].
2. HH is a highly complex model, resulting in high implementation costs and low energy efficiency [20]. On

Manuscript received 12 April, 2024; accepted 8 July, 2024.

This research is supported by the Erciyes University Scientific Research Projects Coordination Unit under Grant No. FDK2022-11506; TUBITAK, the Scientific and Technological Research Council of Turkey under Grant No. TBTK-0039-0783, 2211-A Domestic General Doctorate Scholarship Program under Grant No. 1649B032201035, and 2214-A International Research Scholarship Program (For PhD students) under Grant No. 1059B142201074-2022/2.

the other hand, the FHN model, although simpler in structure, has limited membrane dynamics [22].

3. Although several studies have illustrated that coupling enhances LSR and LVR in nonlinear circuits with bistable *potential wells* [13], [19], [32], there remains a scarcity of research on neural network logic gates [13], [31]. The current preference for gap junction coupling in existing studies limits the versatility of neural network logic gate design, as it overlooks chemical coupling structures that offer flexibility and adaptability.

This paper investigates for the first time the logical vibrational resonance phenomenon in the Izhikevich (IZ) neuron, which has a simple structure, low simulation cost, and large membrane dynamics. Without noise, periodic forcing current with optimum amplitude and frequency, the neuron exhibited logic gate characteristics. First, a three-state aperiodic signal is applied ($I_1 + I_2$) for a single IZ neuron. In addition, other existing studies have only considered models that can perform a two-state logic operation [20], [22], [28]–[31]. However, in this study, the IZ neuron also exhibited the characteristics of a logic gate with multiple inputs ($I_1 + I_2 + I_3$) based on a truth table. In this way, an energy efficient design with high logic operation capability is presented in the literature. Second, since each neuron has a separate activation, a chemically and electrically coupled neural system was developed in which the input sets (I_1, I_2) are applied separately to subneurons as I_1 and I_2. While electrical synapses transmit information very fast, chemical synapses are more flexible [32]. The logic processing capability of electrically coupled HH and FHN based neural systems has been investigated recently and has not yet been sufficiently contributed [29]–[31]. Moreover, a deep literature search did not reveal any work investigating the logic processing capability of a chemically coupled neural system. This study presents for the first time the logic processing capability of a chemically coupled IZ neuron. In this way, the robust logic processing capability of chemically coupled neural systems has been demonstrated. The system, also consisting of neurons as input sets, exhibited a multi-input (I_1, I_2, I_3) logic gate feature.

In this study, we prove that the single, electrically and chemically coupled IZ neuron, which exhibits a wide range of membrane dynamics such as regular spike (RS), tonic spike (TS), fast spike (FS), mixed mode (MM), and spike latency (SL) and is easy to implement due to its simple structure, exhibits both two-state and three-state AND and OR gates. With its multi-input capability, the brain-inspired logic gate design is more energy efficient as fewer neurons will be used to realise logic gates. Furthermore, this work presents the logical operation of a chemically coupled neural system for the first time. Thanks to the chemically coupled IZ neural system, a new generation of multi-input, energy-efficient neural-inspired logic gate models that can process even subthreshold-level inputs has been presented. Our results will have a widespread impact on the design of new brain-inspired logic gates and will enable the design of new computational models.

In this paper, the basics of Izhikevich neuron, neural system, and logic resonance are explained in Section II. Section III describes the results. Section IV discusses the results and conclusions.

II. BACKGROUND

A. Izhikevich Neuron and Neural System

The Izhikevich neuron is a two-dimensional map-based model that mimics more than 20 firing patterns in the neural cortex [33], [34], using the following differential equations:

$$\dot{v} = 0.04v^2 + 5v + 140 - u + I_{bias} + I_{logic} + + I_{force} + I_{synapse}, \quad (1)$$

$$\dot{u} = a(bv - u), \quad (2)$$

$$\tau_s \dot{z} = \left[1 + \tanh\left(S_s\left(v_{pre} - h_s\right)\right)\right](1 - z) - z / d_s, \quad (3)$$

$$v > 30 \text{ mV then } \{v \to c; u \to u + d\}, \quad (4)$$

where v and u are membrane potential and recovery variable, respectively, a is the time scale of the recovery variable, and b defines the sensitivity of the recovery variable to subthreshold fluctuations of the membrane potential. The after-spike membrane potential reset value is c, and the recovery variable reset value is d [33]. I_{logic} is logic input set. The logic operations of neurons can be flexibly determined by the I_{bias} current. When I_{bias} is 1, the neural system performs OR and when I_{bias} is -1, it performs AND. I_{force} = Asin(wt), where A defines the amplitude of the periodic forcing current and w defines its frequency.

Unique synaptic connections connect neurons. A neuron transmits information to another neuron through a synaptic pathway [34]. Synaptic connections can be chemical or electrical [35]. Electrical synapses play an active role in structures that require fast transmission of information, such as reflexes and vision [32]. Because transmission is bidirectional, they regulate neural synchronisation, which is critical for neural diseases such as Schizophrenia, Parkinson's and Epilepsy [35]–[37]. Chemical synapses also have a direct impact on synchronisation, providing the basis for cognitive functions such as learning, memory, cognition, and emotion [38]–[40]. Chemical synapses are also distinguished from electrical synapses by their more flexible and versatile structure [32].

In chemical synapses, $I_{synapse} = k_s(z - z_0)$ is synaptic current, z is the synaptic activation variable, τ_s, h_s, k_s, and z_0 are time delay, threshold parameter for activation of z, play the role of conductance, and reference level of z, respectively. S_s and d_s are responsible for activation and relaxation of z. When $I_{synapse} = 0$, neural activity can be blocked, presynaptic neuron activation does not allow postsynaptic neuron activation to occur, and the neural system displays only a single neuron activation. When $v_{pre} < h_s$, the synapse is inactive and $z \cong 0$. When $v_{pre} > h_s$, the hyperbolic tangent function takes positive, the synapse becomes active, and the postsynaptic neuron is driven by a synaptic current [41]. In electrical synapses, $I_{synapse} = g(v_{pre} - v_{post})$ defines the gap junction synaptic current, and g is the coupling weight [42]. The various structures of the neural system constructed are shown in Fig. 1.

The dynamics of the membranes RS, TS, FS, MM, and SL are selected to analyse the logic behaviour in both single neuron and neural systems. The chemical coupling parameters are $\tau_s = 10$, $h_s = -59$, $k_s = 10$, $z_0 = 0$, $S_s = 1$, and $d_s = 3$, and IZ neuron parameters are given in Table I. These values are constant throughout the study unless otherwise specified.

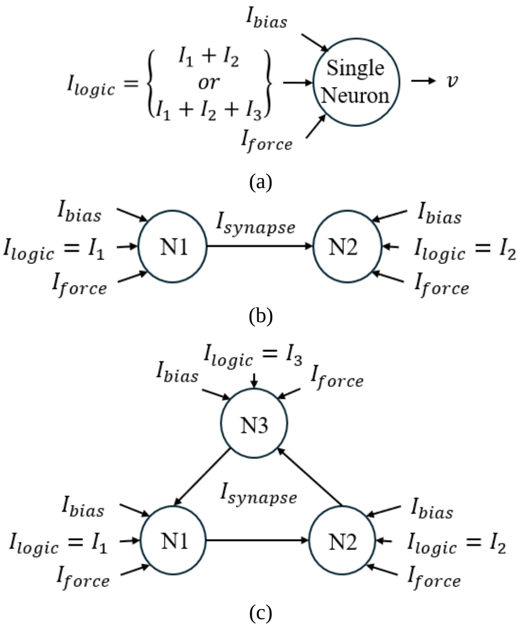


Fig. 1. Examples of neural systems constructed: (a) Single neuron; (b) Two neurons; (c) Three neurons.

TABLE I. NEURON PARAMETERS FOR GENERATING DIFFERENT SPIKING PATTERNS.

Spiking Pattern Type	***a***	***b***	***c***	***d***
Fast Spike	0.1	0.2	-65	2
Mixed Mode	0.02	0.2	-55	4
Regular Spike	0.02	0.2	-65	8
Spike Latency	0.02	0.2	-65	6
Tonic Spiking	0.02	0.2	-60	8

B. Logical Resonance

The logic input-output relationship can be described by encoding N square waves for N inputs. For the single neuron, first, the two logical inputs are I_1 and I_2, where a square wave signal with amplitudes of min -0.5 mV and max +0.5 mV. The current I_{logic}, the sum of two independent signals, results in a three-level aperiodic signal. For a set of inputs, the dynamics of the neuron firing in the direction of a logical output follows the truth tables of AND and OR basic logic operations, as in Table II. The neuron performs the logical operation consistently and robustly only in a periodic force with optimal amplitude and frequency. -1 mV, 0 mV, and +1 mV correspond to (0,0), (0,1)/(1,0), and (1,1), two input logic states, respectively. Second, a three-state logic element is created by applying a third square wave I_3 with the same amplitude as I_1 and I_2. In this case, I_{logic} is a five-level aperiodic signal. Performing the logic operation with one logic element instead of two will result in less energy consumption. The aperiodic input signal I_{logic} is very similar to the input series of the logic element in realisation devices.

TABLE II. TRUTH TABLE OF THE BASIC LOGIC AND AND OR OPERATIONS WITH TWO INPUTS.

I_1 and I_2	**I_{logic}**	**Logical Input Set**	**AND**	**OR**
(-0.5 mV, -0.5 mV)	-1	(0,0)	0	0
(-0.5 mV, 0.5 mV) (0.5 mV, -0.5 mV)	0	(0,1) (1,0)	0	1
(0.5 mV, 0.5 mV)	1	(1,1)	1	1

Coupled neurons are driven separately by logic signals, and the system response is similar to that of a single neuron. The system response is maximised in the presence of a periodic forcing current of appropriate amplitude and frequency. In this study, in addition, unlike other studies, the neuron is driven with a single aperiodic logic input by summing separate logic signals and the input signal is applied to each neuron separately. Due to electrical and chemical coupling, the system response coherently matches a logic process in the presence of periodic force.

It is possible to provide a quantitative proof of the logic processing reliability of the IZ neuron by calculating the probability of producing the desired logic output for different sets of inputs. Comparing the output of the neural system with the expected logical output, the neural system is exposed to many different random inputs in combination over time, and its response to these random inputs is investigated. P is the ratio of correct logic outputs (NSr) to the total number of runs (Nr). For the AND/OR operations, each probability in the truth table is considered successful if it matches the logic output of the neuron for all four input sets. Otherwise, it is regarded as a zero success. The total number of runs is the temporal average of the output obtained against 1250 possible inputs. The fact that a logic gate produces a correct result every time against a large number of inputs tells us about the reliability of the element

$$P = (NSr)/(Nr). \tag{5}$$

If $P(AND)$ or $P(OR)$ is equal to 1, it means that the logic operation is entirely reliable and that the system will produce the correct result for all possible input signals. The logic outputs are required 90 % of the time to follow the expected result. The system can switch between AND and OR by changing the bias current.

III. RESULTS

In this section, it is shown that with the appropriate periodic forcing current, the IZ neuron and neural systems produce output with the correct AND and OR operations. The fourth-order Runge-Kutta method was used in the simulation performed in MATLAB. The step size h = 0.01 and the number of steps N = 1000000 are constant throughout the simulation.

A. Single Neuron

First, the sum of logic input sets $I_{logic} = I_1 + I_2$ is applied to a single IZ neuron. Figure 2 shows the RS, TS, FS, MM, and SL waveforms that the neuron exhibits in response to a three-level input signal. For all waveforms, it is understood that the Izhikevich neuron performs the Logic AND in Fig. 2(a) and the Logic OR in Fig. 2(b).

Second, to obtain a multiple-input logic gate, an input of the form $I_{logic} = I_1 + I_2 + I_3$ was set and applied to the IZ neuron. Figure 3 shows that the IZ neuron performs the logic AND and OR gate with multiple inputs.

The reliability of two- and three-input logic operation of the IZ neuron is directly affected by the amplitude and frequency variation of the periodic forcing current. The variation of the reliability of the IZ neuron for the determined membrane dynamics is given in Fig. 4.

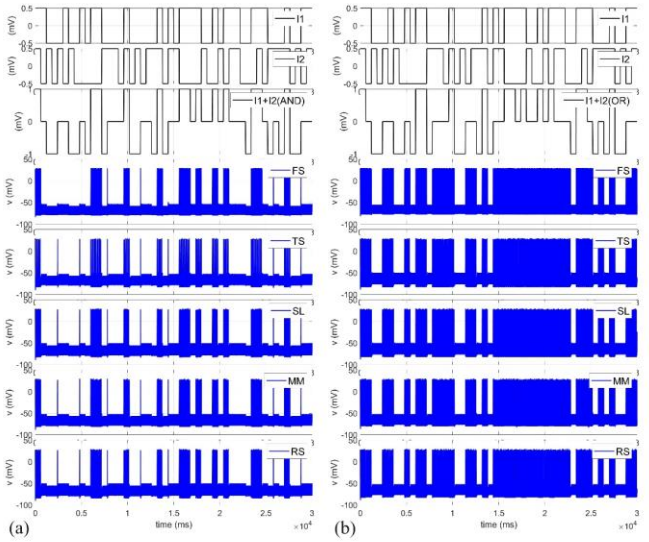


Fig. 2. (a) Logic AND with two inputs, $I_{bias} = -1$, $w = 0.5$, Fast Spike: $A = 8$, Tonic Spiking: $A = 8.5$, Spike Latency: $A = 8.9$, Mixed Mode: $A = 8.6$, Regular Spike: $A = 9$; (b) Logic OR with two inputs, $I_{bias} = 1$, $w = 0.5$, Fast Spike: $A = 6.5$, Tonic Spiking: $A = 8$, Spike Latency: $A = 8$, Mixed Mode: $A = 7.5$, Regular Spike: $A = 7.7$, waveforms generated by the IZ neuron according to the input set $I_{logic} = I_1 + I_2$.

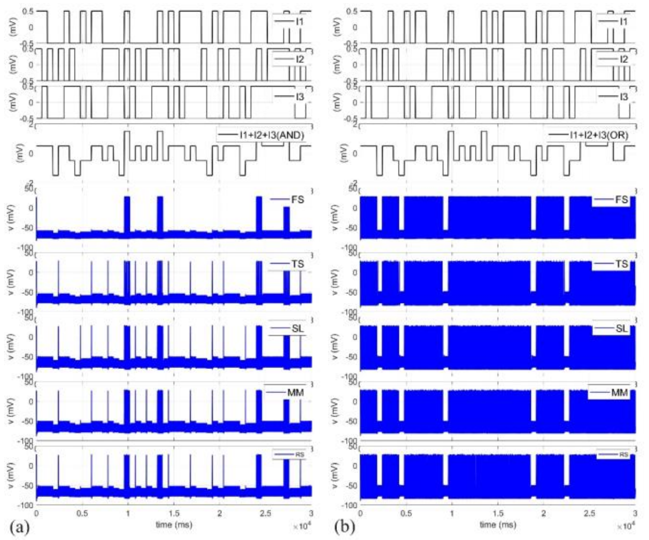
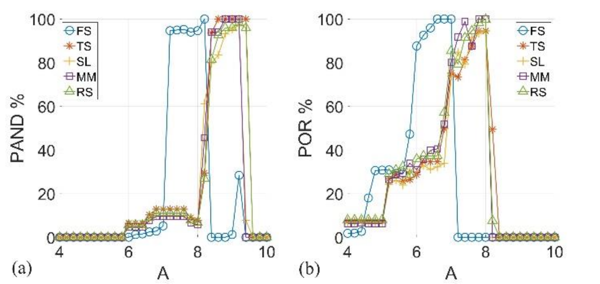


Fig. 3. (a) Logic AND with three inputs, $I_{bias} = -1$, $w = 0.5$, Fast Spike: $A = 6.7$, Tonic Spiking: $A = 7.8$, Spike Latency: $A = 8.6$, Mixed Mode: $A = 8.5$, Regular Spike: $A = 8.2$; (b) Logic OR with three inputs, $I_{bias} = 1$, $w = 0.5$, Fast Spike: $A = 6.9$, Tonic Spiking: $A = 8.8$, Spike Latency: $A = 8.7$, Mixed Mode: $A = 8.5$, Regular Spike: $A = 8.6$, waveforms generated by the IZ neuron according to the input set $I_{logic} = I_1 + I_2 + I_3$.

The logic operation reliability is relatively poor at low values of both the amplitude and frequency of the periodic forcing current. At the optimal amplitude and frequency, the reliability exceeds 90 %. However, continued increases in amplitude and frequency again decreased the reliability. Periodic forcing current is vital to the reliability of the system.



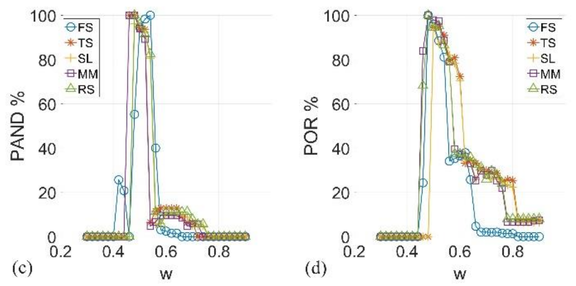


Fig. 4. Graph of the change in logic operation reliability of the IZ neuron as (a) AND, (b) OR with the variation of the amplitude of the forcing periodic current and (c) AND, (d) OR with the variation of the frequency of the forcing periodic current.

B. Electrical Coupling

The logical response of the IZ neural system is investigated. Depending on the number of inputs, multiple inputs force the IZ single neuron to increase from the subthreshold to the superthreshold level due to the increasing logic input amplitude. As a result, unexpected firings occur in IZ single neuron and the reliability of the logic gate decreases. Unlike other studies[13], [31], a coupled IZ neural system is used in this study to avoid this. The IZ neural system demonstrates that neurons provide a collective logic output individually and in cooperation. In addition, the neural system exhibits a largely synchronous behaviour. Coherent logic output was made possible by the synchronous behaviour of the neurons. The fact that there is no need for a separate circuit to add or multiply logic input signals will provide ease for clinical applications.

Here, as shown in Fig. 1(b), logic input I_1 feeds the first neuron and logic input I_2 feeds the second neuron. The output of any interconnected neural system is the output of the logic process (Fig. 5). Throughout the logical process, the membrane dynamics of the neural system is synchronised.

The three-input IZ neural system is shown in Fig. 1(c). Like the two-input system, each neuron is responsible for its logic input. The membrane dynamics of a multi-input IZ neural system is shown in Fig. 6.

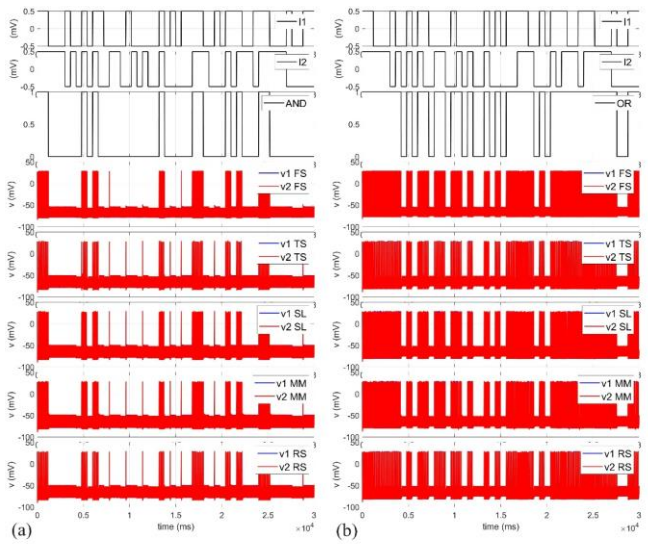


Fig. 5. (a) Logic AND with two inputs, $I_{bias} = -1$, $w = 0.5$, Fast Spike: $A = 8$, Tonic Spiking: $A = 9$, Spike Latency: $A = 9.2$, Mixed Mode: $A = 9.3$, Regular Spike: $A = 9.1$; (b) Logic OR with two inputs, $I_{bias} = 1$, $w = 0.5$, Fast Spike: $A = 6.2$, Tonic Spiking: $A = 7.1$, Spike Latency: $A = 7.2$, Mixed Mode: $A = 7.1$, Regular Spike: $A = 7.2$, waveforms generated by the IZ neuron according to the input set $I_{logic} = (I_1, I_2)$.

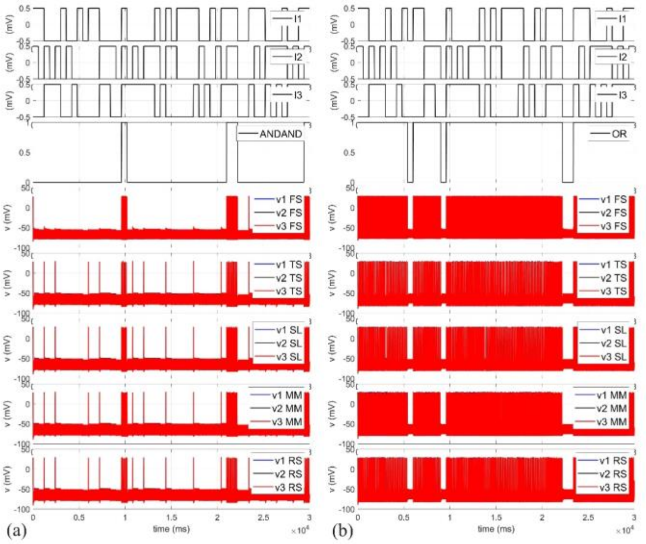


Fig. 6. (a) Logic AND with three inputs, $I_{bias} = -1$, $w = 0.5$, Fast Spike: $A = 7.9$, Tonic Spiking: $A = 8.9$, Spike Latency: $A = 9$, Mixed Mode: $A = 9.1$, Regular Spike: $A = 9.1$; (b) Logic OR with three inputs, $I_{bias} = 1$, $w = 0.5$, Fast Spike: $A = 6.3$, Tonic Spiking: $A = 7.2$, Spike Latency: $A = 7.11$, Mixed Mode: $A = 7.25$, Regular Spike: $A = 7.4$, waveforms generated by the IZ neuron according to the input set $I_{logic} = (I_1, I_2, I_3)$.

The amplitude and frequency of the periodic forcing current are also very important for the IZ neural system (Fig. 7(a)–(d)). At the optimum value, the reliability is at the highest level. However, reliability decreases as we go away from the optimum values. The reliability of the logic operation of the IZ neural system also depends on the synaptic weight (Fig. 7(e)–(f)). A weak connection between neurons makes it challenging to establish neural synchronisation; hence, the reliability of logic processing decreases. The IZ neural system performs logic processing quite robustly at synaptic weight values above a sufficient magnitude.

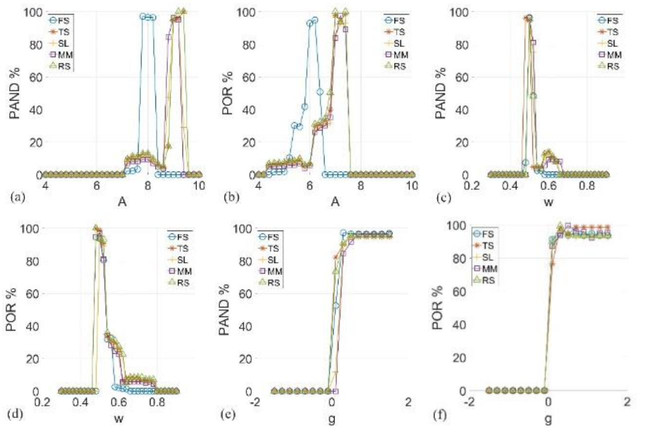


Fig. 7. In the IZ neural system with electrical coupling, with the change in the amplitude of the forcing periodic current (a) AND, (b) OR, with the change of the frequency of the forcing periodic current (c) AND, (d) OR, with the shift in the synaptic weight (e) AND, (f) OR, graph of the change in logic operation reliability.

C. Chemical Coupling

In contrast to electrical coupling, chemical coupling is flexible and versatile [32]. The logic processing capability of the chemically coupled IZ neural system is shown in Figs. 8 and 9. The spike generation points of neurons do not match at some times. Although this situation decreases the logic switch reliability, it is still at an acceptable level, above 90 %, as shown in Fig. 10.

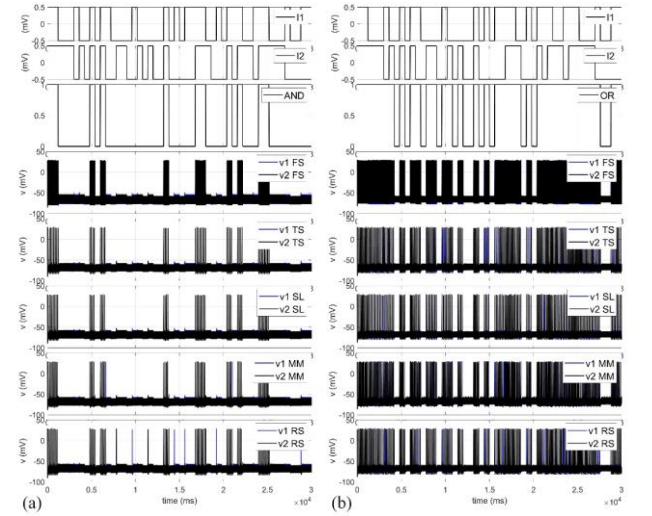


Fig. 8. (a) Logic AND with two inputs, $I_{bias} = -1$, $w = 0.72$, Fast Spike: $A = 9.25$, Tonic Spiking: $A = 8.7$, Spike Latency: $A = 8.7$, Mixed Mode: $A = 8.7$, Regular Spike: $A = 8.9$; (b) Logic OR with two inputs, $I_{bias} = 1$, $w = 0.72$, Fast Spike: $A = 6.9$, Tonic Spiking: $A = 6.7$, Spike Latency: $A = 6.25$, Mixed Mode: $A = 6.74$, Regular Spike: $A = 6.65$, waveforms generated by the IZ neuron according to the input set $I_{logic} = (I_1, I_2)$.

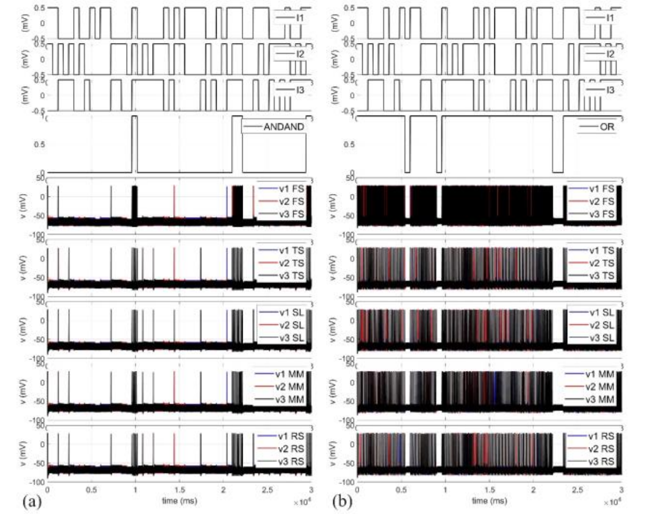


Fig. 9. (a) Logic AND with three inputs, $I_{bias} = -1$, $w = 0.72$, Fast Spike: $A = 9$, Tonic Spiking: $A = 8.9$, Spike Latency: $A = 8.8$, Mixed Mode: $A = 8.9$, Regular Spike: $A = 8.95$; (b) Logic OR with three inputs, $I_{bias} = 1$, $w = 0.72$, Fast Spike: $A = 7$, Tonic Spiking: $A = 6.7$, Spike Latency: $A = 6.7$, Mixed Mode: $A = 6.7$, Regular Spike: $A = 6.7$, waveforms generated by the IZ neuron according to the input set $I_{logic} = (I_1, I_2, I_3)$.

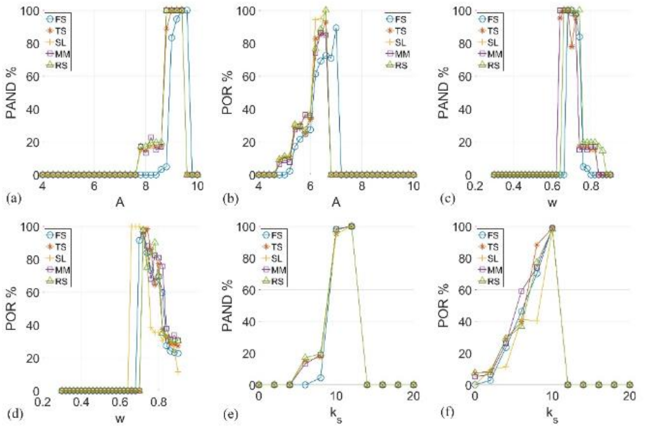


Fig. 10. In the IZ neural system with chemical coupling, with the change in the amplitude of the forcing periodic current (a) AND, (b) OR, with the change of the frequency of the forcing periodic current (c) AND, (d) OR, with the shift in the synaptic weight (e) AND, (f) OR, graph of the change in logic operation reliability.

In chemical coupling, the bond strength between neurons is defined by the synaptic conductance k_s. As k_s changes, the logic operation reliability of the chemically coupled IZ neural system changes. The amplitude and frequency of the forcing periodic current also affect the reliability. Figure 10 shows how the reliability changes for values that are far from the optimum.

IV. DISCUSSION

In this paper, first, a two-state, two-logic signal is summed, and then a three-state, three-logic signal is summed and applied separately as a multi-level logic input to the single IZ neuron. Under a periodic forcing current of appropriate amplitude and frequency, the single IZ neuron exhibited membrane dynamics in response to the logic input. However, the addition of logic inputs may push the neuron above the threshold level, and the neuron may fire uncontrollably. As a result, the reliability of the logic element decreases.

In this case, second, a neural system design, in which logic inputs drive each neuron separately, will avoid this situation. An electrically coupled neural system model that can perform both two-state and three-state logic operations has been developed for this aim. Under the influence of the periodic forcing current, neurons form strong bonds between each other and perform reliable logic processing. Chemical coupling is relatively more flexible and versatile. This study presents the logic processing capability of the IZ neural system model with chemical coupling for the first time. It is also observed that the reliability of the electrically and chemically coupled IZ neural system is reduced if the synaptic connection is insufficient. Table III shows that in addition to the single IZ neuron, electrically coupled and chemically coupled neural systems perform two- and three-state logic AND and OR operations with more than 90 % accuracy. Moreover, high accuracy was achieved in five different membrane dynamics.

TABLE III. LOGIC OPERATION RELIABILITIES OF THE TWO-/THREE-STATE IZ NEURONS, AND IZ NEURAL SYSTEMS WERE OBTAINED USING DIFFERENT MEMBRANE DYNAMICS.

		Single Neuron		**Electrical Coupling**		**Chemical Coupling**	
		Two-State	**Three-State**	**Two-State**	**Three-State**	**Two-State**	**Three-State**
PAND %	**FS**	94.62	93.22	96.45	95.34	96.32	97.56
	TS	93.59	95.23	94.69	96.90	95.23	97.51
	SL	95.18	98.31	94.86	97.22	95.23	96.72
	MM	94.01	97.65	96.31	97.73	98.48	98.68
	RS	95.87	98.97	95.69	95.48	97.75	96.15
POR %	**FS**	96.00	99.37	93.60	93.12	97.41	98.27
	TS	94.53	99.20	98.58	98.94	97.32	97.32
	SL	94.62	98.02	92.97	96.09	98.49	97.06
	MM	97.91	98.05	96.61	98.02	95.31	94.45
	RS	94.47	94.08	93.62	97.82	97.69	93.72

As seen in Table IV, previous studies in the literature focus mostly on bistable systems and two-well potential systems operating as logic elements. The logic element designs of neuron models are quite limited.

TABLE IV. COMPARISON OF PREVIOUS WORKS IN THE LITERATURE AND THE PROPOSED MODEL IN TERMS OF TYPE OF NONLINEAR MODEL, DYNAMIC DIVERSITY OF THE MODEL, SINGLE OR MULTIPLE SYSTEM STRUCTURE, SYNAPSE TYPE, NUMBER OF LOGIC INPUTS, AND LOGIC INPUT CURRENT CALCULATION.

Previous Studies	**Type of Nonlinear Model**	**Dynamic Diversity of the Model**	**Single Model/Network System**	**Sinaps Type**	**Logic State Input**	**Logic Input Current**
Bulsara Bulsara, Dari, Ditto, Murali, and Sinha (2010) [12] Yao and Ma (2020) [18] Zhang, Zheng, Xie, and Song (2017) [19]	Bistable Nonlinear System	Single Dynamic	Single Model	None	Two-State Logic	$I_{logic} = I_1 + I_2$
Yao, Ma, Gui, and Cheng (2021) [17]	Bistable Nonlinear System	Single Dynamic	Single Model Network System	Electrical	Two-State Logic	$I_{logic} = I_1 + I_2$ $I_{logic} = (I_1, I_2)$
Aravind V, Murali, and Sinha (2018) [13] Yang, Yao, and Ren (2022) [21]	Two Bistable Subsystems	Single Dynamic	Network System	Electrical	Two-State Logic	$I_{logic} = I_1 + I_2$
Storni, Ando, Aihara, Murali, and Sinha (2012) [15] Kohar, Murali, and Sinha (2014) [16] Gui, Wang, Yao, and Cheng (2020) [23]	Two-Well Potential System	Single Dynamic	Single Model	None	Two-State Logic	$I_{logic} = I_1 + I_2$
Yao and Ma (2022) [22] Yao (2022) [28] Yao and Yao (2023) [29]	Fitzhugh-Nagumo Neuron	Single Dynamic	Single Neuron	None	Two-State Logic	$I_{logic} = I_1 + I_2$
Deng, Gui, and Yao (2023) [20] Yang and Yao (2023) [30]	Hodgkin-Huxley Neuron	Single Dynamic	Single Neuron	None	Two-State Logic	$I_{logic} = I_1 + I_2$
Yu, Yang, Zhan, Fu, and Jia (2023) [31]	Hodgkin-Huxley Neuron	Single Dynamic	Single Neuron Neural System	Electrical	Two-State Logic	$I_{logic} = I_1 + I_2$ $I_{logic} = (I_1, I_2)$
Proposed Work	*Izhikevich Neuron*	*Five Different Dynamics*	*Single Neuron Neural System*	*Electrical and Chemical*	*Two-State Logic Three-State Logic*	$I_{logic} = I_1 + I_2$ $I_{logic} = (I_1, I_2)$ $I_{logic} = I_1 + I_2 + I_3$ $I_{logic} = (I_1, I_2, I_3)$

Only HH and FHN neuron models have been employed. The HH neuron has a complex structure and requires high design costs. Just like the FHN neuron model, the membrane dynamic diversity is very narrow. In addition, the presented systems perform only a two-state logic operation. Designs with the energy efficiency of three-state logic operation have not been developed. Moreover, the network system models are quite inadequate, and all of them utilise electrical coupling. Chemically coupled neural logic element designs with the advantages of flexibility and versatility have not yet been studied.

However, the results of this study show that the IZ neuron and the neural system eliminate all these limitations. It is demonstrated that the IZ neuron and neural system can exhibit a variety of membrane dynamics with high accuracy, suitable for logic AND and OR operations in response to two- and three-state logic inputs. It is also understood that when the electrically and chemically coupled neural system performs a logic operation with high accuracy, it exhibits high synchronous behaviour, but the reliability of the logic operation decreases with the breakdown of synchronisation, and synchronisation is an important criterion for logic operation.

V. CONCLUSIONS

In this work, it wasa investigate a new generation logic component model based on Izhikevich (IZ) neurons driven by periodic force in the absence of noise, have rich membrane dynamics and are simple in structure. First, the single IZ neuron performs two-state logic AND and OR operations, as well as three-state logic operations, which is different from existing work. The same process can be performed using less logic elements, thus increasing energy efficiency. Second, a neural system consisting of two and three neurons with electrical and chemical coupling design was proposed. Due to the strong connection between them, it has the ability to perform both two- and three-state logic operations. Through the neural system, the cumulative sum of logic input signals in a single neuron is prevented from raising the neuron above the threshold level and generating spikes uncontrollably. In addition to the feature of fast transmission electrical coupling, the neural system also has a chemical coupling structure that differs from electrical coupling because it is flexible and versatile. Our study is likely to make an effective contribution to the insufficient area in the field of neural system logic elements with its chemical coupling feature. Synaptic connectivity has also been shown to directly affect the reliability of logic operation. Because the synaptic weight is not sufficient in electrical coupling and is not in the right range in chemical coupling, the reliability of logic operation has been considerably weakened. From this perspective, the IZ neuron and neural system, in the presence of appropriate periodic forcing current, is likely to have a widespread impact on the field of next generation brain-inspired processing units as a logic element model capable of reliable, multi-input logic operation.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

REFERENCES

[1] S. F. Lempka *et al.*, "Optimization of microelectrode design for cortical recording based on thermal noise considerations", in *Proc. of the 28th IEEE EMBS Annual International Conference*, 2006, pp. 3361–3364. DOI: 10.1109/IEMBS.2006.259432.

[2] P. H. Prajapati and A. D. Darji, "FPGA implementation of MRMN with step-size scaler adaptive filter for impulsive noise reduction", *Circuits, Systems, and Signal Processing*, vol. 39, no. 7, pp. 3682–3710, 2020. DOI: 10.1007/s00034-019-01339-z.

[3] X. Lang, Q. Lu, and J. Kurths, "Phase synchronization in noise-driven bursting neurons", *Physical Review E*, vol. 82, no. 2, p. 021909, 2010. DOI: 10.1103/PhysRevE.82.021909.

[4] J. Bauermann and B. Lindner, "Multiplicative noise is beneficial for the transmission of sensory signals in simple neuron models", *BioSystems*, vol. 178, pp. 25–31, 2019. DOI: 10.1016/j.biosystems.2019.02.002.

[5] X. Shi and Z. Wang, "Stability analysis of fraction-order Hopfield neuron network and noise-induced coherence resonance", *Mathematical Problems in Engineering*, vol. 2020, art. ID 3520972, pp. 1–12, 2020. DOI: 10.1155/2020/3520972.

[6] D. Li, S. Song, and N. Zhang, "Lévy noise-induced inverse stochastic resonance on Newman-Watts networks of Hodgkin-Huxley neurons", *International Journal of Modern Physics B*, vol. 34, no. 19, 2020. DOI: 10.1142/S0217979220501854.

[7] G. Cheng, W. Liu, R. Gui, and Y. Yao, "Sine-Wiener bounded noise-induced logical stochastic resonance in a two-well potential system", *Chaos, Solitons & Fractals*, vol. 131, art. 109514, 2020. DOI: 10.1016/j.chaos.2019.109514.

[8] L. Lu, Y. Jia, M. Ge, Y. Xu, and A. Li, "Inverse stochastic resonance in Hodgkin–Huxley neural system driven by Gaussian and non-Gaussian colored noises", *Nonlinear Dynamics*, vol. 100, no. 1, pp. 877–889, 2020. DOI: 10.1007/s11071-020-05492-y.

[9] D. Petracchi, "What is the role of stochastic resonance?", *Chaos, Solitons & Fractals*, vol. 11, no. 12, pp. 1827–1834, 2000. DOI: 10.1016/S0960-0779(99)00119-8.

[10] P. S. Landa and P. V. E. McClintock, "Vibrational resonance", *Journal of Physics A: Mathematical and General*, vol. 33, no. 45, pp. L433–L438, 2000. DOI: 10.1088/0305-4470/33/45/103.

[11] Z.-Y. He and Y.-R. Zhou, "Vibrational and stochastic resonance in the FitzHugh—Nagumo neural model with multiplicative and additive noise", *Chinese Physics Letters*, vol. 28, no. 11, pp. 110505-1–110505-4, 2011. DOI: 10.1088/0256-307X/28/11/110505.

[12] A. R. Bulsara, A. Dari, W. L. Ditto, K. Murali, and S. Sinha, "Logical stochastic resonance", *Chemical Physics*, vol. 375, nos. 2–3, pp. 424–434, 2010. DOI: 10.1016/j.chemphys.2010.06.015.

[13] M. Aravind V, K. Murali, and S. Sinha, "Coupling induced logical stochastic resonance", *Physics Letters A*, vol. 382, no. 24, pp. 1581–1585, 2018. DOI: 10.1016/j.physleta.2018.03.043.

[14] N. Wang and A. Song, "Enhanced logical stochastic resonance in synthetic genetic networks", *IEEE Transactions on Neural Networks and Learning Systems*, vol. 27, no. 12, pp. 2736–2739, 2016. DOI: 10.1109/TNNLS.2015.2495155.

[15] R. Storni, H. Ando, K. Aihara, K. Murali, and S. Sinha, "Manipulating potential wells in Logical Stochastic Resonance to obtain XOR logic", *Physics Letters A*, vol. 376, nos. 8–9, pp. 930–937, 2012. DOI: 10.1016/j.physleta.2011.12.036.

[16] V. Kohar, K. Murali, and S. Sinha, "Enhanced logical stochastic resonance under periodic forcing", *Communications in Nonlinear Science and Numerical Simulation*, vol. 19, no. 8, pp. 2866–2873, 2014. DOI: 10.1016/j.cnsns.2013.12.008.

[17] Y. Yao, J. Ma, R. Gui, and G. Cheng, "Enhanced logical chaotic resonance", *Chaos*, vol. 31, no. 2, p. 023103, 2021. DOI: 10.1063/5.0037032.

[18] Y. Yao and J. Ma, "Logical chaotic resonance in a bistable system", *International Journal of Bifurcation and Chaos*, vol. 30, no. 13, 2020. DOI: 10.1142/S0218127420501965.

[19] L. Zhang, W. Zheng, F. Xie, and A. Song, "Effect of the correlation between internal noise and external noise on logical stochastic resonance in bistable systems", *Physical Review E*, vol. 96, no. 5, pp. 052203-1–05223-6, 2017. DOI: 10.1103/PhysRevE.96.052203.

[20] H. Deng, R. Gui, and Y. Yao, "Temperature-induced logical resonance in the Hodgkin–Huxley neuron", *Chinese Physics B*, vol. 32, no. 12, p. 120501, 2023. DOI: 10.1088/1674-1056/accd49.

[21] H. Yang, Y. Yao, and J. Ren, "Effect of phase disturbance on logical vibrational resonance", *Chinese Journal of Physics*, vol. 77, pp. 124–133, 2022. DOI: 10.1016/j.cjph.2022.02.012.

[22] Y. Yao and J. Ma, "Logical stochastic and vibrational resonances induced by periodic force in the FitzHugh–Nagumo neuron", *The*

European Physical Journal Plus, vol. 137, no. 11, art. no. 1214, 2022. DOI: 10.1140/EPJP/S13360-022-03423-X.

[23] R. Gui, Y. Wang, Y. Yao, and G. Cheng, "Enhanced logical vibrational resonance in a two-well potential system", *Chaos, Solitons & Fractals*, vol. 138, art. 109952, 2020. DOI: 10.1016/j.chaos.2020.109952.

[24] H. Seok, D. Lee, S. Son, H. Choi, G. Kim, and T. Kim, "Beyond von Neumann architecture: Brain-inspired artificial neuromorphic devices and integrated computing", *Advanced Electronic Materials*, vol. 10, no. 8, pp. 2300839-1–2300839-33, 2024. DOI: 10.1002/aelm.202300839.

[25] C. Jiang *et al.*, "Mammalian-brain-inspired neuromorphic motion-cognition nerve achieves cross-modal perceptual enhancement", *Nature Communications*, vol. 14, art. no. 1344, 2023. DOI: 10.1038/s41467-023-36935-w.

[26] F. Zenke and E. O. Neftci, "Brain-inspired learning on neuromorphic substrates", *Proceedings of the IEEE*, vol. 109, no. 5, pp. 935–950, 2020. DOI: 10.1109/JPROC.2020.3045625.

[27] J. Wang, X. Zhuge, and F. Zhuge, "Hybrid oxide brain-inspired neuromorphic devices for hardware implementation of artificial intelligence", *Science and Technology of Advanced Materials*, vol. 22, no. 1, pp. 326–344, 2021. DOI: 10.1080/14686996.2021.1911277.

[28] Y. Yao, "Logical chaotic resonance in the FitzHugh–Nagumo neuron", *Nonlinear Dynamics*, vol. 107, no. 4, pp. 3887–3901, 2022. DOI: 10.1007/s11071-021-07155-y.

[29] Y. Yao and C. Yao, "Autapse-induced logical resonance in the FitzHugh–Nagumo neuron", *Nonlinear Dynamics*, vol. 111, no. 5, pp. 4807–4821, 2023. DOI: 10.1007/s11071-022-08091-1.

[30] H. Yang and Y. Yao, "Logical stochastic resonance in the Hodgkin–Huxley neuron", *Pramana: Journal of Physics*, vol. 97, no. 2, art. no. 80, 2023. DOI: 10.1007/s12043-023-02551-y.

[31] D. Yu, L. Yang, X. Zhan, Z. Fu, and Y. Jia, "Logical stochastic resonance and energy consumption in stochastic Hodgkin–Huxley neuron system", *Nonlinear Dynamics*, vol. 111, no. 7, pp. 6757–6772, 2023. DOI: 10.1007/s11071-022-08187-8.

[32] N. Kopell and B. Ermentrout, "Chemical and electrical synapses perform complementary roles in the synchronization of interneuronal networks", *Proceedings of the National Academy of Sciences*, vol. 101, no. 43, pp. 15482–15487, 2004. DOI: 10.1073/pnas.0406343101.

[33] E. M. Izhikevich, "Which model to use for cortical spiking neurons?", *IEEE Transactions on Neural Networks*, vol. 15, no. 5, pp. 1063–1070, 2004. DOI: 10.1109/TNN.2004.832719.

[34] E. M. Izhikevich, "Simple model of spiking neurons", *IEEE Transactions on Neural Networks*, vol. 14, no. 6, pp. 1569–1572, 2003. DOI: 10.1109/TNN.2003.820440.

[35] D. Purves *et al.*, *Neurosciences*, 6th ed., Sinauer Associates, 2018.

[36] P. Chawla, S. B. Rana, H. Kaur, K. Singh, R. Yuvaraj, and M. Murugappan, "A decision support system for automated diagnosis of Parkinson's disease from EEG using FAWT and entropy features", *Biomedical Signal Processing and Control*, vol. 79, part 1, art. 104116, 2023. DOI: 10.1016/j.bspc.2022.104116.

[37] K. Tanaka-Koshiyama *et al.*, "Abnormal spontaneous gamma power is associated with verbal learning and memory dysfunction in schizophrenia", *Frontiers in Psychiatry*, vol. 11, art no. 832, 2020. DOI: 10.3389/fpsyt.2020.00832.

[38] T. Womelsdorf and P. Fries, "The role of neuronal synchronization in selective attention", *Current Opinion in Neurobiology*, vol. 17, no. 2, pp. 154–160, 2007. DOI: 10.1016/j.conb.2007.02.002.

[39] *Encyclopedia of the Human Brain*. Academic Press, 2002.

[40] H. C. Krishnan and L. C. Lyons, "Synchrony and desynchrony in circadian clocks: Impacts on learning and memory", *Learning & Memory*, vol. 22, no. 9, pp. 426–437, 2015. DOI: 10.1101/lm.038877.115.

[41] V. B. Yucedag and I. Dalkiran, "Raspberry Pi implementation of the Wilson-Cowan neural network with chemical synapse", in *Proc. of 2023 Innovations in Intelligent Systems and Applications Conference (ASYU)*, 2023, pp. 1–6. DOI: 10.1109/ASYU58738.2023.10296705.

[42] D. E. Postnov, L. S. Ryazanova, and O. V. Sosnovtseva, "Functional modeling of neural-glial interaction", *BioSystems*, vol. 89, nos. 1–3, pp. 84–91, 2007. DOI: 10.1016/j.biosystems.2006.04.012.