Neuromorphic Circuits with Spiking Astrocytes for Increased Energy Efficiency, Fault Tolerance, and Memory Capacitance

Murat Isik
Drexel University
Philadelphia, USA
mci38@drexel.edu

Kaushal Gawri
Semaai
Delhi, India
kaushal.gawri@semaai.com

Maurizio De Pitta
University Health Network
Toronto, Canada
maurizio.depitta@uhnresearch.ca

***Abstract*—In the rapidly advancing field of neuromorphic computing, integrating biologically-inspired models like the Leaky Integrate-and-Fire Astrocyte (LIFA) into spiking neural networks (SNNs) enhances system robustness and performance. This paper introduces the LIFA model in SNNs, addressing energy efficiency, memory management, routing mechanisms, and fault tolerance. Our core architecture consists of neurons, synapses, and astrocyte circuits, with each astrocyte supporting multiple neurons for self-repair. This clustered model improves fault tolerance and operational efficiency, especially under adverse conditions. We developed a routing methodology to map the LIFA model onto a fault-tolerant, many-core design, optimizing network functionality and efficiency. Rigorous evaluation showed that our design is area and power-efficient while achieving superior fault tolerance compared to existing approaches. Our model features a fault tolerance rate of 81.10% and a resilience improvement rate of 18.90%, significantly surpassing other implementations. The results validate our approach in memory management, highlighting its potential as a robust solution for advanced neuromorphic computing applications. The integration of astrocytes represents a significant advancement, setting the stage for more resilient and adaptable neuromorphic systems.**

***Index Terms*—Neural Systems, Fault tolerance, Astrocyte, Hardware, Neuromorphic Computing**

I. Introduction

The field of neuromorphic computing is undergoing a transformative phase, driven by the integration of biologically-inspired components. This paper introduces a groundbreaking approach that integrates the Leaky Integrate-and-Fire Astrocyte (LIFA) model into Spiking Neural Networks (SNNs). SNNs, inspired by brain dynamics, are known for their energy-efficient processing and biologically plausible learning algorithms [1], [2]. However, SNNs remain vulnerable to faults that can impair their efficiency. Astrocytes play a critical role in regulating neuronal activity and synaptic transmission, contributing to the resilience and adaptability of biological networks [3], [4]. This integration of astrocytic mechanisms into SNNs offers dynamic adjustments for fault tolerance [5], [6], [7].

Despite performance improvements, technology scaling brings challenges such as increased power densities and faults in neuron and synapse circuits, affecting model performance and robustness [8], [9]. The LIFA model, rooted in the dynamic interplay between neurons and astrocytes, enhances neural processing by bolstering computational strength and efficiency [10]. This integration also introduces novel computational capabilities into neuromorphic computing [11], [12], [13].

Our methodology targets four pillars: energy efficiency, memory measurement, efficient routing, and fault tolerance. This integration enables accurate emulation of brain functions and marks an advancement in neuromorphic computing by moving beyond traditional neuron-centric models.

A fault-tolerant neuromorphic computing system is proposed, consisting of four components:

- **Alternative Reduce Regime:** Optimizes energy consumption through single neuron component switching, demonstrating a commitment to sustainable and efficient computing.
- **Memory Measurement and Management:** Explores synaptic dynamics inspired by Hopfield networks to optimize memory storage and retrieval, achieving superior memory efficiency with fewer connections.
- **Innovative Routing and Fault Tolerance:** Implements robust routing mechanisms with fault-tolerant strategies, ensuring network integrity and resilience with minimal component usage.
- **LIFA Model Implementation:** Involves adapting astrocytic and neuronal interactions from a theoretical model to a fully functional computational model, offering computational advantages and insights.

We set new benchmarks in energy efficiency, memory management, routing strategies, and fault tolerance. Our methodology, evaluated using various deep learning models, demonstrates efficacy in area and power efficiency while providing robust fault tolerance.

II. Leaky Integrate-and-Fire Astrocyte (LIFA) Model

To understand astrocytic dynamics in neuromorphic computing, we integrate the LIFA model into our system. The LIFA model is motivated by the principle that astrocytic

Ca^{2+} elevations beyond a threshold trigger the release of neuroactive molecules such as glutamate and ATP, called gliotransmitters. These gliotransmitters promote postsynaptic neural activity. Biophysical arguments support that subthreshold Ca^{2+} dynamics set the rate of gliotransmitter-mediated postsynaptic depolarizations. The relevant time constants are τ_N for neuronal activity (v_N), τ_G for astrocytic Ca^{2+} activity (v_G), and τ_p for gliotransmitter dynamics. The ODEs are:

$$\tau_N \frac{dv_N}{dt} = -v_N + I_N(t) \quad (1)$$

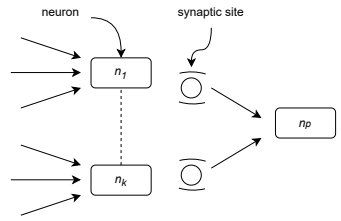
$$\tau_G \frac{dv_G}{dt} = -v_G + I_G(t) \quad (2)$$

$$\tau_p \frac{dg}{dt} = -g + G(1-g)r_G(t) \quad (3)$$

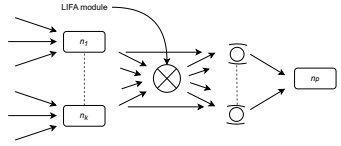
where $I_N(t)$ and $I_G(t)$ are the synaptic inputs to neurons and glia, and $r_G(t)$ is the gliotransmitter release. Synaptic weights (w) are proportional to postsynaptic activation (q), i.e. $w = uq$, and astrocytes contribute to postsynaptic activation by Qg, so $w = u(q_0 + Qg)$, where q_0 is the baseline postsynaptic activation.

Incorporating these aspects of the LIFA model into our framework aims to achieve a more biologically accurate and efficient simulation of astrocyte-neuronal interactions. This enhances the realism of our model and provides a robust foundation for advanced computational strategies.

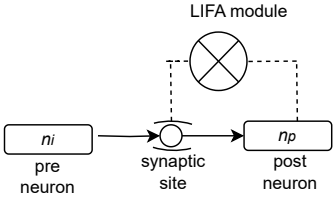
Figure 1 (a) shows a neural network before astrocyte modulation. Figure 1 (b) shows the network after integrating astrocyte modulation, demonstrating structural and functional changes due to astrocyte integration. Figure 1 (c) shows LIFA's operation between synaptic site and post neuron activities. Figure 2 illustrates the network's stages: normal operation, stress, recovery, and potential failure. The black traces show the network's threshold voltage V_{th} under normal conditions, while the red traces show the threshold voltage under stress. Stress refers to conditions that push the network beyond typical operational parameters. Recovery denotes the network's ability to return to normal operation after stress, and v_{spk} refers to the spike voltage that triggers neuron firing, while v_{idle} denotes the idle voltage. The x-axis represents time, and the y-axis, labeled ΔV_{th}, represents the change in threshold voltage, showing the network's stress response and recovery capability over time.



(a) Original network.



(b) LIFA-modulated network.



(c) Operation of LIFA.

Fig. 1. Inserting LIFA in a neural network.

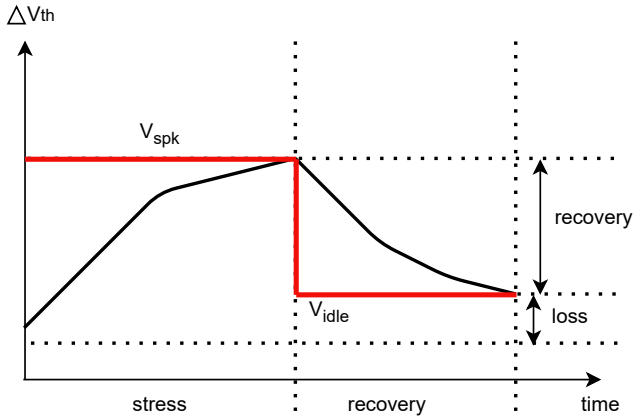


Fig. 2. Self-repair mechanism of an astrocyte.

III. Proposed Design Methodology

We used Python to execute implementations on the CPU and GPU. The study leveraged NVIDIA's GeForce RTX 3060 GPU and Intel's Core i9 12900H CPU for efficient execution. The LIFA model begins with astrocytes receiving external stimuli, such as optogenetic Ca^{2+} uncaging and electrical stimulation of synaptic afferents, which are crucial for initiating astrocytic responses. Astrocytes integrate these stimuli, leading to Ca^{2+} signals essential for gliotransmitter release. This integration phase is influenced by the number, duration, and strength of stimuli.

Figure 3 illustrates modeling, clustering, error tolerance analysis, fault-tolerant hardware implementation, and fault simulation. Astrocytic mechanisms are incorporated into the LIFA model to improve network resilience and error recovery. The baseline design includes training with data, clustering for pattern recognition, error tolerance analysis, and fault injection testing (ARES).

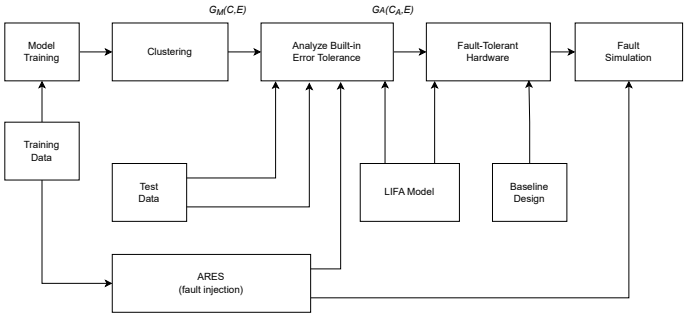


Fig. 3. Schematic representation of the LIFA model.

A. Memory Measurement and Management

This section describes the methodology to assess and optimize memory dynamics within SNNs, based on astrocytic activity's influence on synaptic plasticity and Hopfield network principles.

Astrocyte-Induced Synaptic Dynamics: Astrocytic mechanisms introduced by the LIFA model alter synaptic behavior fundamentally, influencing synaptic plasticity, memory formation, and retrieval.

Memory Capacity and Efficiency: Astrocytic modulation evaluates the memory capacity and efficiency of SNNs, inspired by Hopfield networks known for robust pattern recognition capabilities.

Optimizing Synaptic Connections: Our methodology optimizes the number of synaptic connections, using fewer connections to maintain or enhance memory functionality.

Capacitance Modeling for Memory Updates: We analyze memory design capacitance within the SNN, calculating updates due to astrocyte-mediated synaptic modulation. This includes SRAM, DRAM, and memristor-based synaptic arrays, determining the capacitance for storing and updating a bit or synaptic weight.

The LIFA model's integration into SNNs represents an innovative approach to memory measurement and management, leveraging astrocytic functions for enhanced efficiency and capacity in neuromorphic computing.

B. Innovative Routing and Fault Tolerance

Figure 4 shows how clustered neural networks integrate astrocyte-like structures. Astrocytic modulation pathways or the flow of information is evident in each cluster, representing neurons or nodes in a neural network. This figure illustrates astrocyte integration in neural networks, enhancing computational abilities or resilience. Clusters with similar functions are interconnected, mirroring biological neural networks. Algorithm 1 outlines the integration of astrocytes into an inference model G_M, structured into clusters 0 to 6. For each cluster, the algorithm applies the ARES framework to introduce N_r random errors, evaluating the model's accuracy after each error. If the accuracy a_{min} falls below the threshold a_{th}, an astrocyte is added to the cluster. The process iterates

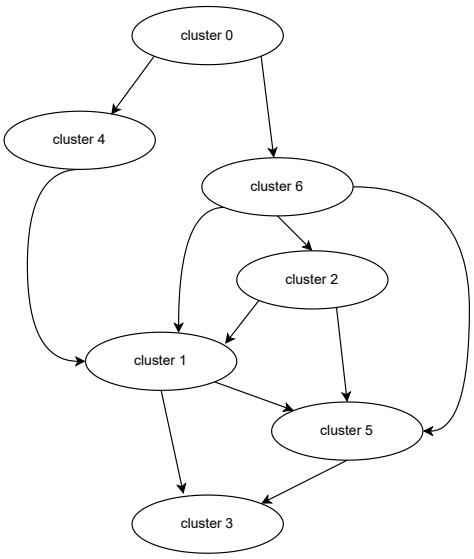


Fig. 4. Astrocyte Integrated Clustering.

across all clusters, balancing neuron distribution across multiple astrocytes. Parameters N_r and a_{th} are user-defined, with typical settings of 10,000 and baseline model accuracy a_o. This ensures model robustness against accuracy degradation due to errors.

$$
\begin{aligned}
G_M(C,E) &= \text{Inference model with } C \text{ clusters and } E \text{ edges} \\
G_A(C_A,E) &= \text{Astrocyte-enabled model with } C_A \text{ clusters and } E \text{ edges} \\
L &= \text{Layers of a core. } L=\{L_x,L_y\} \text{ and } L=\{L_x,L_y,L_z\}
\end{aligned}
$$

We set an accuracy constraint, $a_{th} = a_0$, indicating a hardware failure induces a model error if the accuracy drops from the baseline. This guides the co-design approach from Algorithm 1. For each astrocyte-enabled cluster $C_j \in C_A$ of G_A, we design a crossbar/μBrain core tailored to the astrocyte-augmented layers. We fix the number of astrocytes per core, leveraging their frequency reconstruction property. Aiming for an average spike frequency of 2.17 Hz and a maximum reconstruction error of 10%, our configuration requires 4452 neurons per astrocyte. Post-implementation on the FTN cores, unused astrocytes are disabled to optimize fault tolerance rate.

C. Alternative Reduce Regime for Energy Consumption

This section describes optimizing energy consumption in neuromorphic systems using the LIFA model, inspired by astrocytes' energy-efficient neurotransmitter release and calcium signaling processes. Astrocytes in the brain conserve energy while maintaining optimal neural activity. LIFA aims to replicate this efficiency in SNNs, reducing network energy consumption through single neuron component switching. This approach controls neuron activity precisely, enhancing overall SNN efficiency and contributing to energy savings. Incorporating LIFA into SNNs underscores our commitment to efficient and sustainable computing paradigms. Analyses and tests determine the effectiveness of the alternative reduce

Algorithm 1: Algorithm for integrating astrocytes into a clustered SNN model.

Input: $G_M = (\mathbf{C}, \mathbf{E})$
Output: $G_A = (\mathbf{C}_A, \mathbf{E})$
for $C_k \in C$ **do** /* For each cluster in C */
  Arrange C_k into layers based on clustering shown in Fig. 4 ;
  /* E.g., $C_k = \{C_k^0, C_k^1, \ldots\}$ for each cluster. */
  for $C_k^i \in C_k$ **do** /* For each layer in C_k */
    while *(true)* **do** /* Run until all neurons of the layer are protected against errors */
      Insert N_r random errors using ARES and evaluate the minimum accuracy a_{min};
      if $a_{min} < a_{th}$ **then** /* Min accuracy is less than threshold. */
        $C_k^i = C_k^i \cup$ A; /* Add an astrocyte to the layer. */
      else
        exit;
  /* Astrocytes are mapped based on the clustering to optimize fault tolerance. */

regime, quantifying energy savings using metrics like energy consumption per task and spike event. We compare traditional computational models with LIFA to demonstrate its ability to reduce SNN energy consumption through improved efficiency.

IV. Evaluation

Our evaluation of our proposed neuromorphic architecture is focused on the following pivotal components. A comprehensive suite of applications spanning machine learning, data analytics, and signal processing are used to test our system. Through this diverse workload spectrum, we are able to thoroughly analyze our architecture's adaptability and performance across a wide range of scenarios, ensuring its versatility in handling a variety of computational tasks. Our simulation framework consists of the following.

- `PyTorch [14]`: for astrocyte modeling.
- `ARES [15]`: for fault simulations.
- `pyJouleS [16]`: for hardware results.

A. Energy Efficiency Assessment

In this section, we delve into the energy efficiency of SNN with a focus on the LIFA model.

- **Energy Consumption Analysis:** The energy consumption of the SNN was meticulously analyzed, both with and without the implementation of the Alternative Reduce Regime (ARR). This analysis concentrated on quantifying energy use on a per-neuron and per-synaptic operation basis. As illustrated in Figure 5, the LIFA Model demonstrates a significant variation in energy consumption contingent on the employment of the ARR.
- **Performance-Energy Trade-off:** A critical evaluation of the LIFA model was conducted to discern the interplay between energy-saving strategies and overall SNN performance. This assessment probed into whether there exists a discernible trade-off between achieving energy efficiency and maintaining or enhancing computational speed and accuracy.

The complex connectivity inherent in the LIFA model, characterized by a high density of neuron-neuron synapses within clusters, underlines the model's potential inemulating the intricacies of biological neural networks.

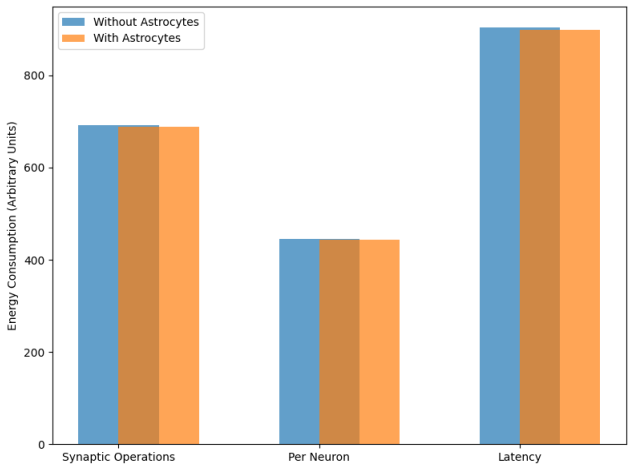


Fig. 5. LIFA Model Energy Consumption.

B. Memory Management Effectiveness

This section focuses on evaluating the memory management effectiveness of the LIFA model, particularly in the context of SNNs.

- **Memory Utilization:** Our analysis focused on comparing the LIFA model's total memory utilization with that of conventional SNNs. This comparative study particularly highlighted the effect of optimized synaptic connections in the LIFA model. As evidenced in Figure 6, the innovative synaptic connection optimization in LIFA explains its superior memory efficiency. Besides reducing the memory footprint, this optimization also increases the network's overall computational efficiency.
- **Pattern Storage and Retrieval Accuracy:** Our tests in LIFA were analogous to those conducted in Hopfield networks to assess its memory capabilities. We conducted these tests to evaluate how well the model stored and retrieved patterns. LIFA exhibits high accuracy in both pattern storage and retrieval, surpassing traditional SNNs. An application requiring high precision in pattern recognition and recall can benefit greatly from the model's advanced memory management techniques.

A pivotal aspect of our evaluation is the use of memory capacity as a relative measure, ranging from 0 (no recall) to 1 (perfect recall). A neuromorphic uses this approach to assess its efficiency by comparing input patterns to their subsequent recalls. A comprehensive framework for modeling complex interactions within neural networks is provided by the LIFA model, which incorporates neuron and astrocyte activity. As a result of this integration, the model has enhanced memory capabilities as well as a better understanding of the interplay between various neural components, resulting in a more accurate neuromorphic simulation.

TABLE I
LIFA HYPERPARAMETERS.

Parameters		Values	
2-arachidonyl glycerol (2-AG), AG	0	Indirect signal to the synaptic site, ESP)	0
Direct signaling pathway, DSE	0	Glutamate Rate, GLU	0
Rate of Production of AG	0.1s	Rate of Production Glutamate	0.1s
Rate of Decay Glutamate	0.1s	Rate of Decay ESP	0.1s
Scaling Factor of ESP	0.1	Equivalent Reset Potential, v_{r_G}	0.2
Equivalent Firing threshold, v_{t_G}	1.0	Ca2+ time constant, τ_G	0.5s
Absolute Refractory Period, τ_{r_G}	0.1s	Resting release probability(exc. synapses), u_0	0.3
Fraction of shared synapses, f	0.5	Excitatory PSP (on neurons), J	0.4mV
Equivalent Excitatory PSP (on astrocytes), W	1.8×10^{-3}	Presynaptic activity rates, v_S	30Hz
Gliotransmitter release probability, u_G	1.0	Strength of gliotransmission, G	0.05
Polarity of gliotransmission,ξ	0.8	Decay time constant, τ_p	10s
Ca signal- Cystolic Calcium	0.2	Last spike time, $last\_spike\_time$	0
Time constant for Ca^{2+} decay, τ	0.4	Threshold for spike firing, $threshold$	0.5
Refractory period after spike firing, $refractory\_period$	0.5s	Gain for VDCC, $vdcc\_gain$	0.1
Gain for IP3 receptors, $ip3\_gain$	0.1	Astrocyte Activity, $activity$	[1...10]
External Stimuli/Input bias, $external\_input$	0	Astrocyte Time Scale, $astrocyte\_time\_scale$	0.10
Synapse to Astrocyte Connection Weights	[1...10]	Time constant, τ	20
Neuron resting membrane potential, V_{rest}	70mV	Reset potential, v_{reset}	-70mV
Firing threshold, $V_{\text{threshold}}$	-50mV	Absolute refractory period, $T_{\text{refactory}}$	0ms
Initial Firing Rate, $firing\_rate$	1	Neuron Firing Threshold, $firing\_threshold$	Random value
Resting release probability (exc. synapses), u_0	0.3	Fraction of shared synapses, f	0.5
Neuronal Activity, $activity$	[1...10]	External stimul/input bias, $external\_input$	0
Neuron characteristic time scale, τ_n	0.10	Synpatic connection weights	[1...10]
Number of synapses, $num\_synapses$	10		

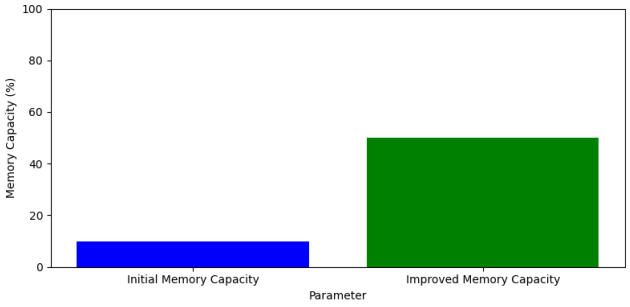


Fig. 6. Memory Management.

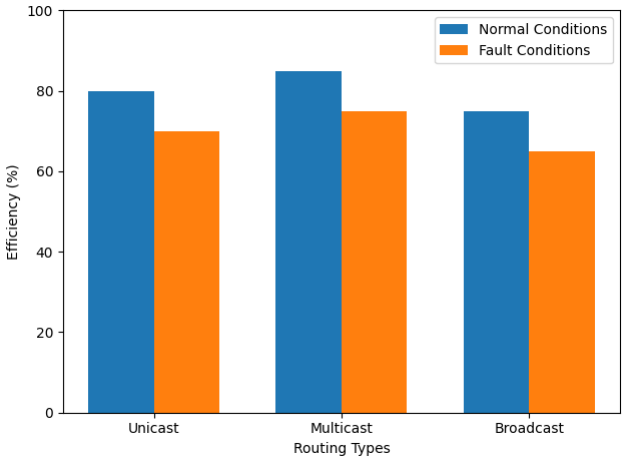


Fig. 7. Routing Efficiency under Normal and Fault Conditions.

C. Routing Mechanisms and Fault Tolerance

An assessment of the fault tolerance capabilities of the system's LIFA is conducted in conjunction with an examination of the efficiency of different routing mechanisms within a SNN.

Routing Efficiency: The efficiency and speed of various routing algorithms, namely unicast, multicast, and broadcast, have been rigorously evaluated both under normal and fault conditions. Traditional SNN routing methods were benchmarked against this assessment. As depicted in Figure 7, routing types vary significantly in performance, with multicast routing generally displaying the best resilience. Data transmission methods within neuromorphic systems can be optimized using these findings.

Fault Tolerance Analysis: We systematically introduced faults into the SNN to assess its robustness and continuity of operation. Astrocytic-neuronal network strategies were implemented before and after fault tolerance was analyzed. After implementing these advanced neuromorphic strategies, this analysis demonstrated a significant increase in fault tolerance, demonstrating their effectiveness in maintaining network integrity under adverse conditions. A fault tolerance rate of 63.11% was initially demonstrated by the SNN without astrocytes. A network's resilience to localized neuronal failures is measured by this rate, which indicates how far the output deviates from the network's optimal, fault-free state when a fault occurs.

Fault tolerance improved significantly when astrocyte-

neuronal strategies were implemented. The network's fault tolerance rate was improved to 81.10% after integration. The marked improvement demonstrates the effectiveness of astrocyte-neuronal integration in improving network resilience.

The fault tolerance (FT) of the SNN is defined as:

$$FT = \frac{O_{\text{fault}} - O_{\text{original}}}{O_{\text{original}}} \times 100\% \tag{4}$$

where O_{original} is the output in the fault-free state, and O_{fault} is the output under fault conditions.

The values for our SNN model are:

$$FT_{\text{astro-initial}} = 63.11\%$$

$$FT_{\text{astro-LIFA}} = 81.10\%$$

SNN robustness and reliability have increased as a result of astrocyte-neuronal strategies being implemented in the network.

D. Comparative Analysis

A comparative analysis between our proposed system and traditional single-node neuromorphic systems validates the effectiveness of our approach. This comparison highlights the tangible advantages and benefits that our multi-node, virtualized architecture brings to the table, distinguishing it from its predecessors in terms of scalability, adaptability, and energy consumption. LIFA results are highlighted in Table II.

TABLE II
LIFA RESULTS.

Metric	**Value**
Neurons	4452
Synapses	6918144
Network Topology	1024, 768, 2048, 512, 100
Network Recovery	18.90%
Fault Tolerance Rate	81.10%
Model Complexity (MAC)	6.9 M
Average Spike Frequency	2.173 Hz
Latency	9.038 sec
Throughput	492.56 neurons/sec

Throughput, spike frequency, neural network utilization, and LIFA model overhead will be measured quantitatively in order to assess the performance of our proposed architecture. These metrics will be evaluated under various operational conditions and configurations to provide a clear, objective assessment of the system's overall performance and efficiency, highlighting its strengths and areas for potential improvement.

TABLE III
COMPARISONS WITH STATE OF ART IMPLEMENTATIONS.

	Wei et al. [17]	Johnson et al. [18]	Isik et al. [5]	Isik (2023) et al. [8]	**Our**
Neurons	2	14	336	680	**4452**
Synapses	1	100	17,408	69,888	**6918144**
Network Recovery	30%	30%	39%	27.92%	**18.90%**
Fault Tolerance Rate	12.5%	70%	51.6%	63.11%	**81.10%**
Power	-	1.37 W	0.538 W	2 W	-

Table III provides a comprehensive comparison of our proposed implementation with several prior works in the field of astrocyte modeling. The table highlights key aspects such as the number of neurons and synapses, fault tolerance rate, and resilience improvement, offering insights into the complexity and robustness of each model. Our implementation stands out with its significantly higher neuron count (4452) and synapse count (6918144), which are considerably higher than those in other referenced works. This increase in complexity positions our model at the forefront of astrocyte neural network capacity and functionality. In terms of fault tolerance rate, our model achieves an impressive 81.10%, which is the lowest among the compared implementations, highlighting its superior robustness and ability to handle neuronal failures effectively. Additionally, the network recovery of our model is 18.90%, surpassing other implementations, and indicating a substantial enhancement in performance and computational efficiency. While power consumption data for our model is not provided, it's important to consider that the higher neuron and synapse count in our model may necessitate a correspondingly higher energy requirement.

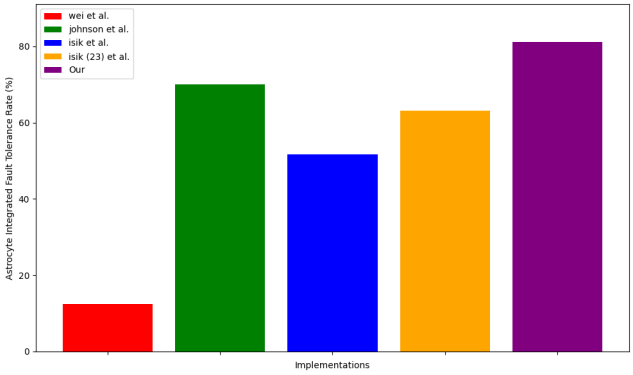


Fig. 8. Fault Tolerance Rate Comparison.

Figure 8 presents a comparative analysis of fault tolerance rates across various neuromorphic computing implementations. This comparison includes state of art implementations and our implementation. The chart highlights the percentage of fault tolerance for each study, showcasing how each values in maintaining network integrity under fault conditions. Notably, our implementation demonstrates a significant improvement in fault tolerance, with the lowest rate among the compared studies.

V. CONCLUSIONS

We presented a design methodology for the LIFA model, focusing on integrating astrocytes into neural network models. Our approach involved a core architecture of neurons, synapses, and astrocyte circuits, where each astrocyte encloses multiple neurons for self-repair in case of neuron failure. This innovative design significantly enhances the system's fault tolerance, maintaining efficiency and robustness under adverse conditions. The incorporation of astrocytes creates a

dynamic and resilient network, capable of adapting to neuron failures. We developed a routing methodology to map the LIFA model onto the fault-tolerant many-core design, optimizing the network's functionality and efficiency. Our rigorous evaluation demonstrated that the design is both area and power-efficient, achieving superior fault tolerance compared to existing approaches. Specifically, our model showed a fault tolerance rate of 81.10% and a network recovery rate of 18.90%, significantly outperforming other state-of-the-art implementations. The integration of astrocytes marks a significant advancement in the field, paving the way for more resilient and adaptable neuromorphic systems.

REFERENCES

[1] P. K. Huynh, M. L. Varshika, A. Paul, M. Isik, A. Balaji, and A. Das, "Implementing spiking neural networks on neuromorphic architectures: A review," *arXiv preprint arXiv:2202.08897*, 2022.

[2] R. V. W. Putra, M. A. Hanif, and M. Shafique, "Softsnn: Low-cost fault tolerance for spiking neural network accelerators under soft errors," in *Proceedings of the 59th ACM/IEEE Design Automation Conference*, 2022, pp. 151–156.

[3] A. Ben Abdallah and K. N. Dang, "Fault-tolerant neuromorphic system design," in *Neuromorphic Computing Principles and Organization*. Springer, 2022, pp. 127–154.

[4] W. Y. Yerima, O. M. Ikechukwu, K. N. Dang, and A. B. Abdallah, "Fault-tolerant spiking neural network mapping algorithm and architecture to 3d-noc-based neuromorphic systems," *IEEE Access*, 2023.

[5] M. Isik, A. Paul, M. L. Varshika, and A. Das, "A design methodology for fault-tolerant computing using astrocyte neural networks," in *Proceedings of the 19th ACM International Conference on Computing Frontiers*, 2022, pp. 169–172.

[6] S. Haghiri and A. Ahmadi, "Digital FPGA implementation of spontaneous astrocyte signalling," *IJCTA*, 2020.

[7] A. P. Johnson, D. M. Halliday, A. G. Millard, A. M. Tyrrell, J. Timmis, J. Liu, J. Harkin, L. McDaid, and S. Karim, "An FPGA-based hardware-efficient fault-tolerant astrocyte-neuron network," in *SSCI*, 2016.

[8] M. Isik and K. Inadagbo, "Astrocyte-integrated dynamic function exchange in spiking neural networks," in *International Conference on Engineering of Computer-Based Systems*. Springer, 2023, pp. 263–273.

[9] S. R. Kumar and S. Singhal, "Implementation of neuron astrocyte interaction dynamics," in *2023 IEEE 8th International Conference for Convergence in Technology (I2CT)*. IEEE, 2023, pp. 1–6.

[10] M. De Pittà and N. Brunel, "Multiple forms of working memory emerge from synapse–astrocyte interactions in a neuron–glia network model," *Proceedings of the National Academy of Sciences*, vol. 119, no. 43, p. e2207912119, 2022.

[11] L. Kozachkov, J.-J. Slotine, and D. Krotov, "Neuron-astrocyte associative memory," *arXiv preprint arXiv:2311.08135*, 2023.

[12] M.-L. Linne, J. Aćimović, A. Saudargiene, and T. Manninen, "Neuron–glia interactions and brain circuits," in *Computational Modelling of the Brain: Modelling Approaches to Cells, Circuits and Networks*. Springer, 2022, pp. 87–103.

[13] Y. Pan and M. Monje, "Neuron–glial interactions in health and brain cancer," *Advanced biology*, vol. 6, no. 9, p. 2200122, 2022.

[14] S. Imambi, K. B. Prakash, and G. Kanagachidambaresan, "Pytorch," *Programming with TensorFlow: Solution for Edge Computing Applications*, pp. 87–104, 2021.

[15] B. Reagen, U. Gupta, L. Pentecost, P. Whatmough, S. K. Lee, N. Mulholland, D. Brooks, and G.-Y. Wei, "Ares: A framework for quantifying the resilience of deep neural networks," in *DAC*, 2018.

[16] M. C. Belgaid, "Green coding: an empirical approach to harness the energy consumption ofsoftware services," Ph.D. dissertation, Université de Lille, 2022.

[17] X. Wei, C. Li, M. Lu, G. Yi, and J. Wang, "A novel astrocyte-mediated self-repairing cpg neural network," in *2019 Chinese Control Conference (CCC)*. IEEE, 2019, pp. 4872–4877.

[18] A. P. Johnson, J. Liu, A. G. Millard, S. Karim, A. M. Tyrrell, J. Harkin, J. Timmis, L. McDaid, and D. M. Halliday, "Homeostatic fault tolerance in spiking neural networks utilizing dynamic partial reconfiguration of fpgas," in *2017 International Conference on Field Programmable Technology (ICFPT)*. IEEE, 2017, pp. 195–198.