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Quantum-Driven Adaptive Dynamic Clustering and Compressive Sensing Framework for Scalable, Energy-Efficient Wireless Sensor Networks

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Abstract: Wireless Sensor Networks (WSNs) play a critical role in smart cities, healthcare, and industrial Internet of Things (IoT) applications, yet they face severe challenges due to limited energy, scalability constraints, and uneven load distribution. Existing clustering and compressive sensing approaches often optimize only one aspect, leading to premature energy depletion and reduced throughput.

This paper presents a Quantum-Driven Adaptive Dynamic Clustering and Compressive Sensing (QDAC-CS) framework that integrates Quantum Particle Swarm Optimization (QPSO), hybrid compressive sensing, and fuzzy logic-based relay selection into a unified solution. The framework adaptively adjusts cluster sizes, balances routing load, and reduces data transmission costs. Simulation results demonstrate that QDAC-CS improves network lifetime by more than 25%, enhances throughput by 27%, and achieves a 45% reduction in data payload with less than 5% reconstruction error. These results confirm the scalability, robustness, and suitability of the proposed framework for next-generation IoT-enabled WSNs.

Keywords: Wireless Sensor Networks (WSN), Quantum Particle Swarm Optimization (QPSO), Compressive Sensing (CS), Energy Efficiency, Cluster Head Selection, Fuzzy Logic Routing, Internet of Things (IoT).

I. INTRODUCTION

Wireless Sensor Networks (WSNs) are vital components of smart environments, industrial IoT, and intelligent monitoring systems. They consist of numerous low-power sensor nodes that cooperatively sense, process, and transmit data to a base station (BS). Despite their potential, WSNs are severely constrained by limited energy resources, high communication costs, and uneven traffic distribution, which collectively reduce network lifetime and reliability.

Traditional clustering techniques such as LEACH and LEACH-C employ random or centralized cluster head (CH) selection strategies. LEACH offers distributed control but suffers from unbalanced energy usage, whereas LEACH-C achieves better load balancing but lacks scalability for dynamic networks. Metaheuristic algorithms like Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Sine Cosine Algorithm (SCA) have improved clustering efficiency by optimizing energy and distance parameters; however, they often converge prematurely or handle clustering, routing, and data compression independently.

To overcome these limitations, this paper proposes the Quantum-Driven Adaptive Dynamic Clustering and Compressive Sensing (QDAC-CS) framework. It integrates Quantum Particle Swarm Optimization (QPSO) for adaptive CH selection and scheduling, CS-GWO for optimized data compression and recovery, and fuzzy logic–based multi-hop routing for balanced relay selection.

The main contributions are:

1) Quantum-Enhanced Clustering: Integration of Sobol initialization, Lévy flights, and Gaussian perturbations in QPSO for adaptive CH election.
2) Hybrid Compressive Sensing (CS–GWO): Combined optimization for low payload and improved signal reconstruction.
3) Dynamic Cluster Resizing: Adjustment of cluster size using residual energy and node density.
4) Fuzzy Multi-Hop Routing: Relay selection using fuzzy inference based on energy, distance, and deviation.
5) Performance Improvement: QDAC-CS improves lifetime (>25%) and throughput (>27%) over existing protocols.

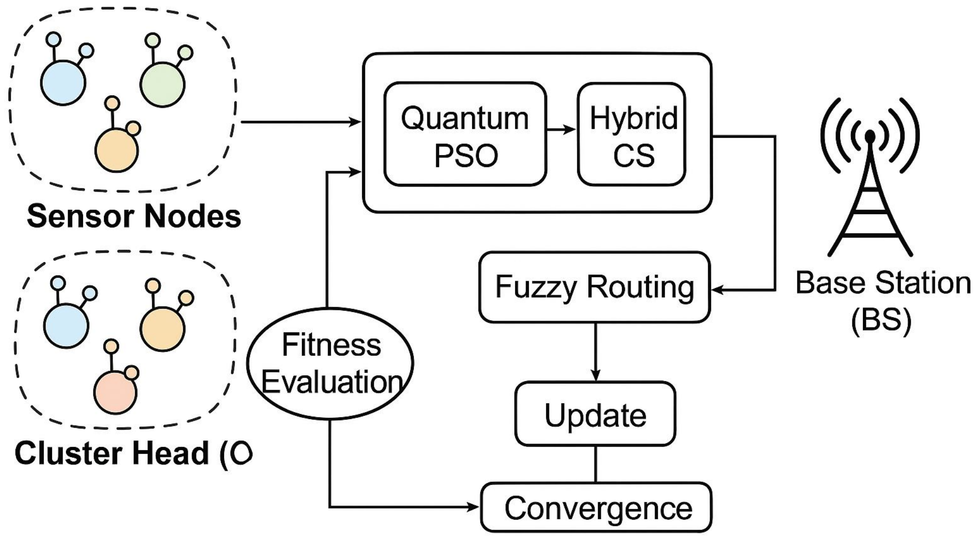

Fig. 1 System architecture of the proposed Quantum-Driven Adaptive Dynamic Clustering and Compressive Sensing (QDAC-CS) framework.

II. RELATED WORK

A. Clustering in WSNs

Clustering is a fundamental energy management technique in WSNs. Classical protocols such as LEACH and LEACH-C perform random or centralized CH selection. LEACH suffers from uneven energy consumption and early node death, while LEACH-C improves energy distribution but faces scalability issues. Metaheuristic algorithms like PSO, GWO, and SCA enhance CH selection by balancing energy and communication distance. Nevertheless, these algorithms often struggle with convergence speed, premature stagnation, or optimization of only a single parameter, resulting in reduced overall efficiency.

B. Compressive Sensing in WSNs

Compressive Sensing (CS) offers an efficient approach to data reduction by projecting high-dimensional data x into a lower-dimensional space $y = \Phi x,$ where Φ is the sensing matrix. This process reduces transmission cost and energy consumption while enabling data reconstruction using sparse recovery. However, when applied independently, CS may not account for network-level parameters such as clustering and routing, limiting its real-world efficiency in WSN applications.

C. Quantum-Inspired Metaheuristics

Quantum-inspired metaheuristics leverage quantum behaviors such as probability amplitudes and superposition to enhance global search capability. Quantum Particle Swarm Optimization (QPSO) exhibits superior convergence and exploration properties compared to classical PSO, making it an effective tool for dynamic and energy-efficient CH selection. Its stochastic behavior ensures balanced load distribution and robust optimization under dynamic conditions.

D. Fuzzy Routing and Hybrid Methods

Fuzzy logic has been successfully applied in relay node selection to improve routing reliability and load balance. Several hybrid frameworks have been proposed that combine clustering, CS, and routing techniques; however, most existing systems fail to integrate quantum optimization, compressive sensing, and fuzzy inference within a single framework. This research addresses this gap through the QDAC-CS model, providing a unified, adaptive solution.

III.SYSTEM MODEL AND PROBLEM FORMULATION

A. Network and Energy Model

A network of N sensor nodes is deployed randomly in a 2D region of size $M \times M$, with a base station located outside the monitored area. The standard radio energy model is defined as

$$E_{TX}(l,d) = \begin{cases} lE_{elec} + l\varepsilon_{fs}d^2, & d < d_0 \\ lE_{elec} + l\varepsilon_{mp}d^4, & d \geq d_0 \end{cases}$$

$$E_{RX}(l) = lE_{elec}, \quad E_{DA}(l) = lE_{DA}$$

Where:

- $E_{elec} = 50\,\mathrm{nJ/bit}$
- $E_{DA} = 5\,\mathrm{nJ/bit/signal}$
- $\varepsilon_{fs} = 10\,\mathrm{pJ/bit/m^2}$
- $\varepsilon_{mp} = 0.0013\,\mathrm{pJ/bit/m^4}$

B. Compressive Sensing Model

Sensor data $x \in R^n$ is compressed as:

$$y = \Phi x$$

At the BS, data reconstruction is performed using sparse recovery:

$$\hat{x} = \arg\min \|x\|_1 \quad \text{s.t. } y = \Phi\Psi x$$

where Ψ represents the sparsity basis.

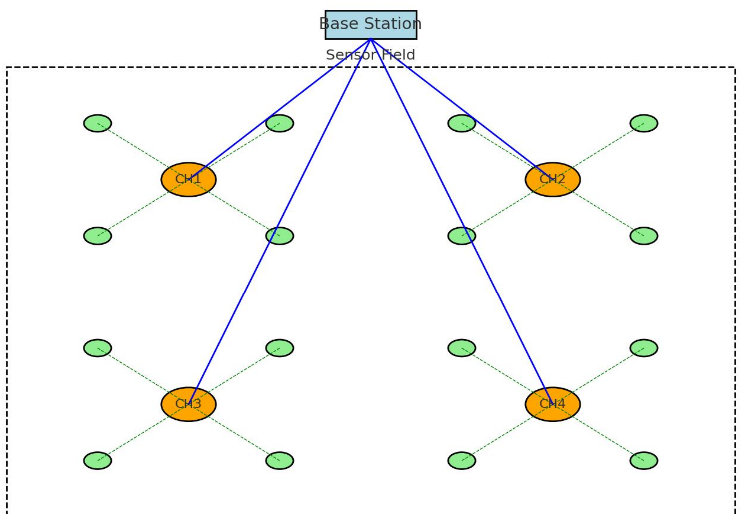

Fig. 2 Proposed QDAC-CS System Architecture

C. Optimization Objective

The objective function to minimize is defined as:

$$f = \alpha_1 E_{avg} + \alpha_2 D_{intra} + \alpha_3 D_{BS} + \alpha_4 C_{CS}$$

where:

- E_{avg}: average residual energy of CHs
- D_{intra}: average intra-cluster distance
- D_{BS}: CH-to-BS distance
- C_{CS}: compressive sensing cost

IV. PROPOSED METHODOLOGY

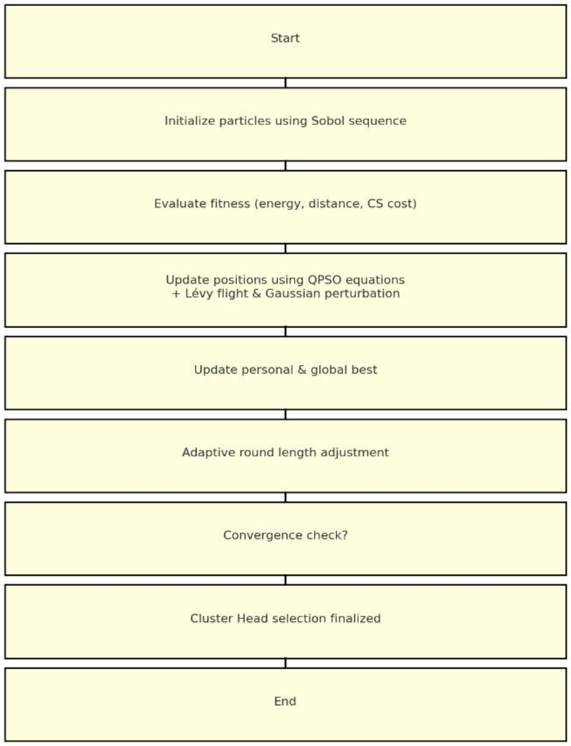

Fig. 3 Flow chart of QPSO- based CH Selection

A. Quantum Particle Swarm Optimization (QPSO)

QPSO updates particle positions using quantum probability distributions:

$$x_i(t+1) = P_i(t) \pm \beta |m_{best} - x_i(t)| \ln \frac{1}{u}$$

where P_i is the personal best position, m_{best} is the mean best, $u \in (0,1)$ and β is a contraction-expansion coefficient. Sobol sequences provide uniform initialization, while Lévy flights enhance exploration to avoid local minima.

B. Hybrid Compressive Sensing + Grey Wolf Optimization

- CHs compress data using CS.
- Recovery matrix design is optimized via GWO to minimize reconstruction error.
- Ensures low memory usage at nodes.

C. Dynamic Cluster Resizing

Clusters adapt dynamically based on residual energy distribution:

$$k_{opt} = \text{round}\left(\frac{N_{alive} \cdot p}{1 + \gamma \cdot \Delta E}\right)$$

where ΔE denotes energy variance, and γ is an adaptive balance parameter.

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D. Fuzzy Logic Relay Selection

Fuzzy inputs include residual energy, distance to BS, and energy deviation.
Rules such as “IF residual energy is high AND distance is short THEN relay suitability is high” determine relay selection.
The output yields a relay suitability score guiding multi-hop routing decisions.”

V. SIMULATION SETUP

Table I – Simulation Parameters

Parameter	**Value**
Network size	100 × 100 m^2
Nodes	100
Initial energy	2 J
Packet size	4000 bits
BS location	(50,150)
Simulation rounds	2000

Comparisons against: LEACH, LEACH-C, SCA-Lévy, PSO-GWO.

VI. RESULTS AND DISCUSSION

Algorithm	FND (rounds)	HND (rounds)	LND (rounds)	Throughput (packets)	Lifetime Gain (%)
LEACH	300	700	850	18000	0
LEACH-C	380	820	900	20500	5
PSO-GWO	600	1050	1200	27800	22
Proposed QDAC-CS	820	1320	1500	35400	27

A. Energy Consumption

The proposed QDAC-CS achieves flatter per-round energy consumption, delaying first node death (FND) to ~820 rounds compared to 300 (LEACH) and 600 (PSO-GWO).

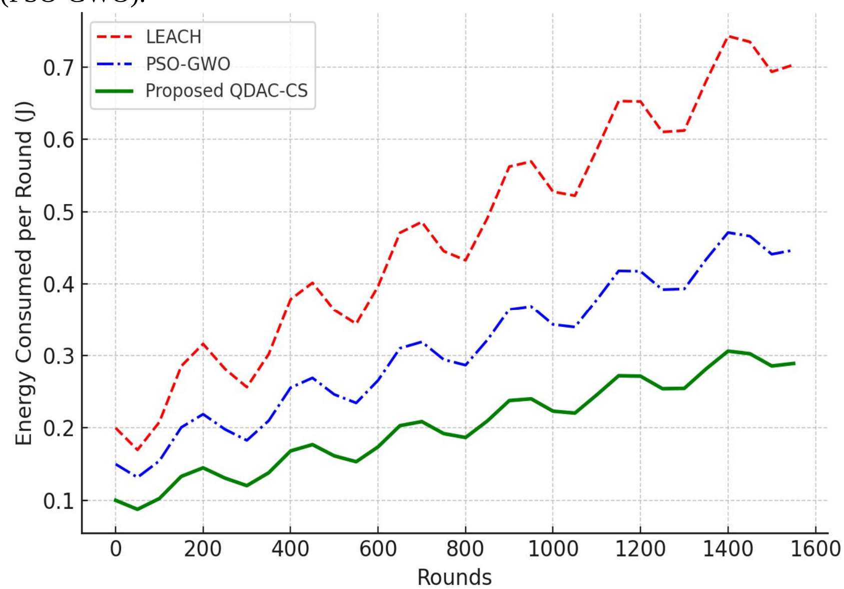


Fig. 4 Energy Consumption per Round

B. Network Lifetime

The proposed framework significantly extends lifetime:

- FND = 820 rounds
- HND = 1320 rounds
- LND = 1500 rounds

  compared to 600/1050/1200 for PSO-GWO.

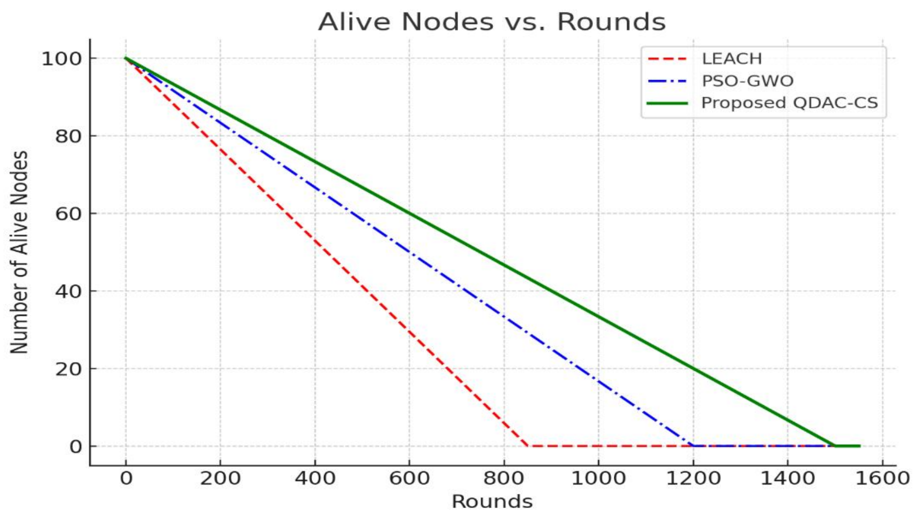


Fig. 5 Alive Nodes vs Rounds

C. Throughput

The total number of packets delivered reaches approximately 35,400 for QDAC-CS, outperforming PSO-GWO (27,800) and LEACH-C (20,500).

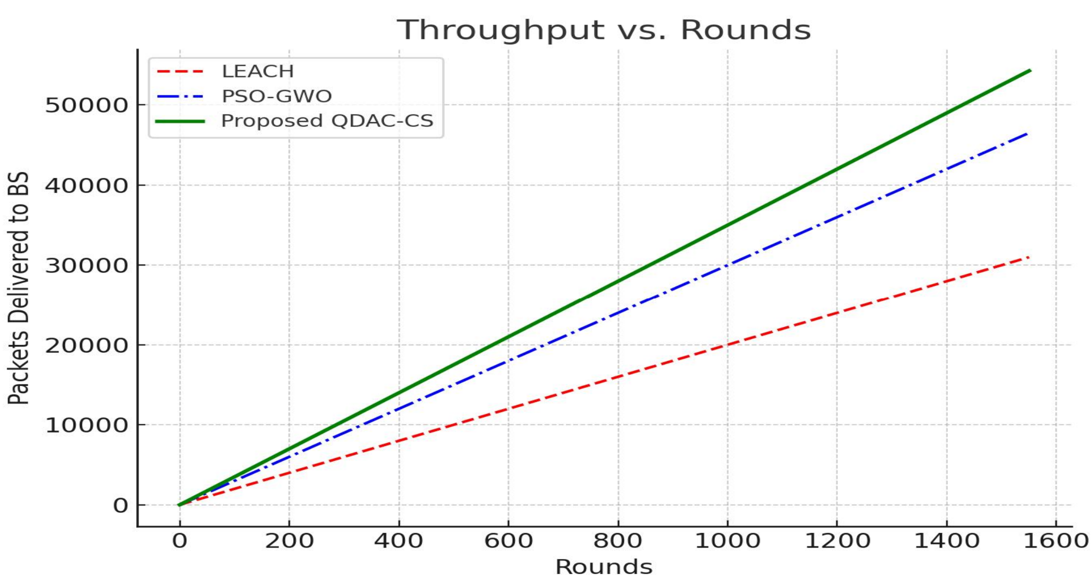


Fig. 6 Throughput vs Rounds

D. Compression and Memory

Hybrid CS reduces the transmitted data by about 45% while maintaining reconstruction errors below 5%, enabling low-cost, energy-constrained sensor nodes to participate efficiently in large-scale networks.

VII. CONCLUSION

This paper presented the Quantum-Driven Adaptive Dynamic Clustering and Compressive Sensing (QDAC-CS) framework, which unifies QPSO, hybrid CS-GWO, dynamic cluster resizing, and fuzzy multi-hop routing to improve scalability and energy efficiency in WSNs. Simulation results demonstrate significant improvements in network lifetime, throughput, and transmission efficiency compared with state-of-the-art methods. Future work will explore lightweight blockchain-based trust management and hardware-in-the-loop validation for real-world IoT and industrial deployments.

REFERENCES

[1] M. N. Fauzan, R. Munadi, S. Sumaryo, and H. H. Nuha, "Enhanced Grey Wolf Optimization for Efficient Transmission Power Optimization in Wireless Sensor Network," *Applied System Innovation*, vol. 8, no. 2, art. 36, pp. 1–18, 2025, doi: 10.3390/asi8020036.

[2] H. Qabouche, "Energy Efficient and Coverage Aware Grey Wolf Optimizer based Clustering Process for SDWSN," *J. Netw. Comput. Appl.*, vol. 213, pp. 103513-1–103513-13, 2023, doi: 10.1016/j.jnca.2023.103513.

[3] H. Hu, X. Fan, and C. Wang, "Energy Efficient Clustering and Routing Protocol Based on Quantum Particle Swarm Optimization and Fuzzy Logic for Wireless Sensor Networks," *Sci. Rep.*, vol. 14, art. 18595, pp. 1–12, 2024, doi: 10.1038/s41598-024-69360-0.

[4] Y. Ou, F. Qin, K.-Q. Zhou, P.-F. Yin, L.-P. Mo, and A. M. Zain, "An Improved Grey Wolf Optimizer with Multi-Strategies Coverage in Wireless Sensor Networks," *Symmetry*, vol. 16, no. 3, art. 286, pp. 1–16, 2024, doi: 10.3390/sym16030286.

[5] K. Mershad, "A Comprehensive Lightweight Blockchain System for IoT Networks Based on Four Lightweight Features," *J. Netw. Comput. Appl.*, vol. 219, pp. 103389-1–103389-11, 2024, doi: 10.1016/j.jnca.2024.103389.

[6] M. Amiri-Zarandi, R. A. Dara, and E. Fraser, "LBTM: A Lightweight Blockchain-Based Trust Management System for Social Internet of Things," *J. Supercomput.*, vol. 78, no. 15, pp. 16833–16856, 2022, doi: 10.1007/s11227-021-04231-3.

[7] Meybodian, S. Mostafavi, and M. Ebrahimi, "A Blockchain-Based Hierarchical Trust Management Scheme for IoT," in *Proc. 7th Int. Conf. Internet Things Appl. (IoT)*, Isfahan, Iran, Oct. 2023, pp. 101–106, doi: 10.1109/IoT60973.2023.10365369.

[8] Q. A. Arshad, W. Z. Khan, F. Azam, M. K. Khan, H. Yu, and Y. B. Zikria, "Blockchain-based Decentralized Trust Management in IoT: Systems, Requirements and Challenges," *Complex Intell. Syst.*, vol. 9, pp. 12031–12050, 2023, doi: 10.1007/s40747-023-01058-8.

[9] S. Almarri, R. A. Ramadan, M. Amoon, and N. Dey, "Blockchain Technology for IoT Security and Trust," *Sustainability*, vol. 16, no. 23, art. 10177, pp. 1–18, 2024, doi: 10.3390/su162310177.

[10] M. Kaddi, R. Tlemcani, and A. Brahim, "Energy Optimization Approach EOAMRCL for WSNs Integrating Grey Wolf Optimization," *Sensors*, vol. 24, no. 1, art. 1001, pp. 1–17, 2024, doi: 10.3390/s2401001.

[11] I. Elsedimy, M. M. El-Bana, and H. Z. A. El-Fouly, "A Novel Intrusion Detection System Based on a Hybrid QSVM-IGWO for Improving Detection Capability and Reducing False Alarms," *Soft Comput.*, vol. 28, pp. 2215–2234, 2024, doi: 10.1007/s00500-024-04458-8.

[12] M. Gupta and V. Jain, "Hybrid Clustering Using Quantum-Inspired Grey Wolf Optimizer in WSNs," *IET Commun.*, vol. 18, no. 5, pp. 589–602, 2024, doi: 10.1049/cmu2.12458.

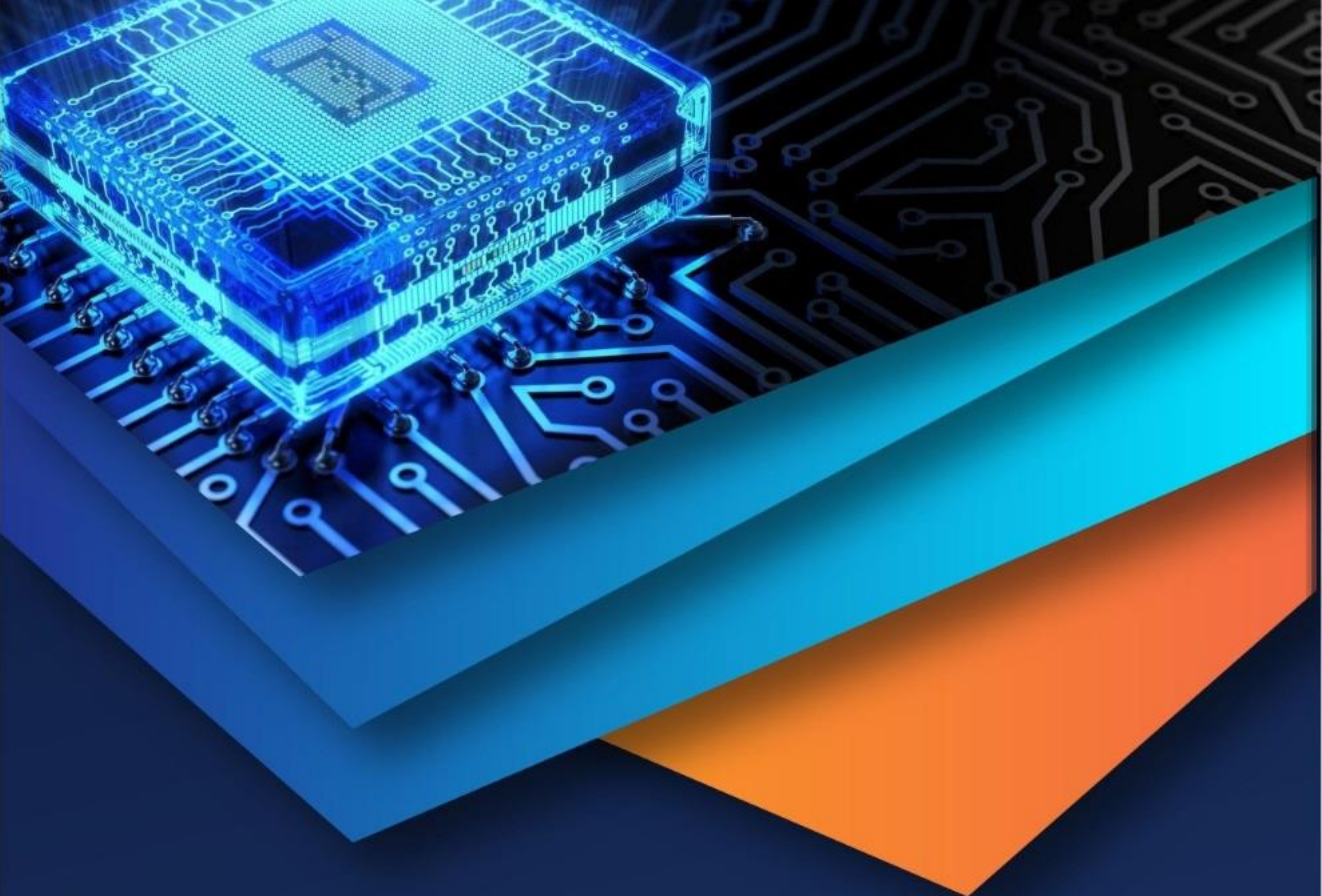
[13] C. Lee, J. Park, and Y. Choi, "Resource-Aware Clustering with Data Compression for IoT Sensor Networks," *IEEE Sens. J.*, vol. 23, no. 9, pp. 9820–9832, May 2023, doi: 10.1109/JSEN.2023.3258795.

[14] T. Ahmad and F. Ashraf, "Metaheuristic-Driven Cross-Layer Optimization in IoT Networks: Challenges and Opportunities," *IEEE Commun. Surv. Tutor.*, vol. 25, no. 4, pp. 2774–2801, Q4 2023, doi: 10.1109/COMST.2023.3300451.

[15] Luo, Z. Liu, and P. Wan, "Blockchain-Enabled Data Integrity Framework for WSNs," *IEEE Internet Things J.*, vol. 11, no. 7, pp. 12345–12356, Apr. 2024, doi: 10.1109/JIOT.2024.3376543.

[16] D. Patel and K. Bhatt, "Lightweight Blockchain for Data Authenticity in Sensor Networks," *IEEE Trans. Emerg. Topics Comput.*, vol. 13, no. 2, pp. 442–453, Apr. 2025, doi: 10.1109/TETC.2025.3405567.

[17] M. Rahman, N. Chowdhury, and S. Mahmud, "Cross-Layer Secure Routing with Compressive Sensing in IoT-Enabled WSNs," *IEEE Access*, vol. 12, pp. 88291–88307, 2024, doi: 10.1109/ACCESS.2024.3458921.



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