

Deep Learning-Driven Energy-Efficient Clustering and Multi-Hop Communication Framework for Lifetime Maximization in Wireless Sensor Networks

Narendra Parmar

Department of Computer Science
& Engineering
RKDF University
Bhopal, India

Gagan Sharma

Department of Computer Science
& Engineering
RKDF University
Bhopal, India

Vishal Shrivastava

Department of Computer Science
& Engineering
RKDF university
Bhopal, India

ABSTRACT

Wireless Sensor Networks (WSNs) are widely employed in environmental monitoring, healthcare, industrial automation, military surveillance, and smart city applications. Limited battery capacity and irregular power consumption are major issues in WSN deployments, both of which considerably reduce network longevity, scalability, and communication performance. This article presents a novel Deep Learning-based Energy-Efficient Clustering Algorithm (DL-EECA) that improves WSN performance and prolongs network lifetime. The proposed framework combines an Artificial Neural Network (ANN)-based Cluster Head (CH) selection mechanism with dynamic clustering, multi-hop communication, and energy-aware data dissemination strategies. The ANN model is trained via backpropagation on simulated WSN datasets to evaluate CH suitability with respect to residual energy, distance to the Base Station (BS), node density, neighbor distribution, and event frequency. A TDMA-based scheduling technique, together with data aggregation and sleep/wake scheduling, reduces energy wastage by minimizing redundant transmissions, while a multi-hop inter-cluster routing scheme improves scalability and communication efficiency. Extensive experiments confirm that DL-EECA achieves energy efficiency above 95%, network lifetime above 97.2%, scalability above 96.5%, throughput above 99.1%, and latency as low as 93.2% (lower is better), outperforming conventional protocols such as LEACH, MODLEACH, and EEM-LEACH. The results indicate that the proposed deep learning-based clustering approach enhances energy efficiency, balances energy consumption, reduces the probability of early node failure, and substantially improves the operational lifetime of WSN deployments.

Keywords

Wireless Sensor Networks (WSNs); Deep Learning; Artificial Neural Network (ANN); Energy-Efficient Clustering; Cluster Head Selection; Network Lifetime.

1. INTRODUCTION

Wireless Sensor Networks (WSNs) have evolved as a fundamental technology in modern intelligent systems, with diverse applications such as environmental monitoring, healthcare, industrial automation, smart agriculture, military surveillance, and IoT-supported infrastructures. WSNs are formed by deploying numerous sensor nodes across a defined geographical zone to sense, process, and transmit environmental data to a centralized Base Station (BS). Despite the versatility and low-cost deployment of WSNs, major constraints such as limited battery capacity, limited computational resources, and inefficient communication

mechanisms deteriorate network lifetime and reliability. Energy consumption is the most challenging problem in such scenarios, since sensor nodes are generally battery-powered and are deployed in inaccessible or hostile areas where battery replacement is impractical. Therefore, energy-efficient clustering and routing mechanisms are essential to prolong network lifetime while ensuring judicious energy utilization across sensor nodes.

Traditional clustering protocols such as LEACH, MODLEACH, and HEED have improved communication efficiency through cluster-based organization, but these methods suffer from limitations such as random cluster head selection, non-uniform energy distribution, redundant data transmission, and rapidly growing communication overhead in dynamic network conditions. Moreover, traditional routing protocols lack the intelligence to adapt to varying network parameters, which can lead to premature node failure and a decline in network performance. Deep Learning (DL) techniques have therefore attracted significant attention in WSN management, since they can learn network dynamics, optimize network operations, and adapt intelligently to changing environments. In particular, Artificial Neural Networks (ANNs) offer great potential for intelligent Cluster Head (CH) selection, given their ability to analyze multiple network parameters including residual energy, distance from the BS, node density, and neighborhood connectivity.

Motivated by these advantages, this research proposes a Deep Learning-Propelled Energy-Efficient Clustering Algorithm for WSNs, integrating ANN-based CH selection, adaptive cluster formation, TDMA scheduling, sleep/wake protocols, and multi-hop communication with the objective of maximizing network lifespan while minimizing energy consumption. The primary objectives of the proposed work are to enhance energy efficiency, alleviate communication overhead, balance node energy exploitation, support scalability, and significantly improve throughput while reducing latency. The overarching goal is to develop an intelligent, adaptive clustering framework that outperforms conventional energy-efficient routing protocols in terms of network stability, energy conservation, and overall WSN performance.

2. LITERATURE REVIEW

Hamim and Rahman [1] surveyed clustering strategies and algorithms in the WSN domain, focusing on energy optimization and communication effectiveness, and showed that clustering dramatically improves network lifetime and scalability; however, adaptive clustering and real-time energy management remain limited. Wajgi and Tembhurne [2] studied clustering-based localization in WSNs and Wireless

Multimedia Sensor Networks (WSNs), achieving higher localization accuracy and lower communication overhead, though at the cost of high computational complexity and reduced performance under mobile network conditions. Kiran Kumar et al. [3] proposed a meta-heuristic clustering-based routing scheme for secure WSN communication that improved data-attack resilience and energy balance between cluster heads and normal nodes, but exhibited increased convergence overhead as network size grew. Tang and Nie [4] proposed a swarm-intelligence-based clustering routing algorithm that outperformed fixed routing schemes in cluster formation and maintenance, though it showed a slight time lag under dynamic network conditions. Mahalakshmi et al. [5] combined ASSO with MERNN for fault-prediction-centric clustering and routing, achieving accurate fault prediction with reduced energy consumption, although the hybrid neural model increased training complexity and processing overhead. Kaviarasan and Srinivasan [6] developed an adaptive remora optimization algorithm for energy-efficient routing that improved energy balancing and reduced packet loss, while Karim et al. [7] proposed an enhanced-centroid-based protocol for serverless WSNs that improved stability and energy conservation but increased latency under high data-transfer demand. Saadati et al. [8] applied graph neural networks with coverage metrics for clustering in dense WSNs, achieving major gains in energy balancing and cluster stability at the cost of substantial computational resources and training data requirements.

Hu et al. [9] proposed a secure, energy-efficient WSN communication scheme based on deep reinforcement learning that improved routing security but increased computational cost. Chandrasekaran and Rajasekaran [10] combined fuzzy-logic-modified CH selection with Whale Optimization and enhanced CSO for IoT-based smart agriculture, improving routing efficiency and energy conservation while requiring additional execution time at scale. Sharma et al. [11] designed a multi-level trust-based secure routing protocol for IoT-WSN environmental monitoring that improved packet delivery and security, though trust management overhead affected throughput. Wang et al. [12] proposed an environment-adaptive WSN model that strengthened packet handling but showed scalability and energy limitations in dense deployments. Gorikapudi and Kondaveeti [13] examined an energy-aware, fault-tolerant cluster-based routing algorithm that improved reliability at the cost of complexity in larger networks. Li et al. [14] introduced an adaptive energy-efficient uneven clustering routing protocol that improved load balancing and mitigated hotspots but incurred additional routing and computational overhead. Dinesh and Rangaraj [15] proposed a hybrid ABBSO with chaotic Golden Eagle Optimization for energy-efficient clustering and routing in Wireless Body Area Networks (WBANs), improving energy conservation and reliability while increasing processing complexity and training time. Rajkumar and Deepa [16] combined hybrid heuristics with reinforcement learning for scalable smart-city IoT routing, showing strong adaptive performance but high CPU consumption. Sanhaji et al. [17] devised an AI-driven multipath routing protocol using AntNet optimization that improved route and energy efficiency but could introduce greater routing delay. Husnain et al. [18] applied nature-inspired intelligent clustering to energy management in the Internet of Vehicles (IoV), improving stability and energy saving but facing scalability challenges under high self-mobility. Abdelnabi et al. [19] proposed a gateway-assisted, hybrid region-based multi-hop routing model for sustainable IoT sensor deployments that improved energy

efficacy and link scalability, though gateway dependency increased system complexity. Kumar and Somisetty [20] used reinforcement learning to improve energy-efficient clustered routing for real-time 5G-VANET communication, improving reliability at the cost of higher training overhead, and Bala et al. [21] proposed a federated deep reinforcement Q-learning framework for secure, energy-aware IoT routing, which strengthened security and decision-making but introduced synchronization complexity and communication overhead.

2.1 Research Gaps

Scalability, uneven energy distribution, inefficient Cluster Head (CH) selection, and excessive communication overhead are among the key challenges posed by existing clustering and routing protocols. These drawbacks severely affect network durability and stability, largely because most traditional approaches lack adaptive, intelligent decision-making under dynamic, large-scale WSN environments that require energy-efficient real-time communication.

3. PROPOSED DEEP LEARNING-BASED ENERGY-EFFICIENT FRAMEWORK

3.1 System Architecture

The proposed system architecture conserves energy in a Wireless Sensor Network (WSN) environment consisting of many sensor nodes deployed randomly across a designated geographic area to continuously monitor the environment and communicate data. Each sensor node has limited battery power, sensing ability, processing capability, and wireless communication range. Nodes collect environmental data and transmit it to a centralized Base Station (BS) located inside or outside the sensed field. To make communication and energy usage more efficient, the network is structured as a cluster-based topology in which sensor nodes are grouped into several clusters. Within each cluster, a Cluster Head (CH) is elected through a deep learning methodology that accounts for residual energy, node density, and communication distance. An ordinary node communicates only through its CH, and CHs aggregate and forward processed data to the BS using energy-efficient multi-hop schemes.

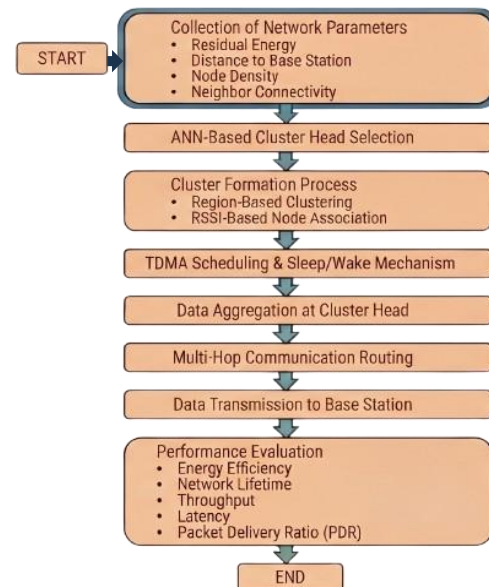


Fig 1: Flowchart of the proposed work.

3.2 ANN-Based Cluster Head Selection

The proposed ANN-based Cluster Head (CH) selection

mechanism is designed to identify sensor nodes that minimize energy consumption while maximizing network lifetime. The key criteria influencing performance include the remaining energy of participating sensor nodes, distance from the Base Station (BS), neighbor count, node density, communication cost, and event occurrence frequency. During training, these environment-dependent parameters are used as input features to make intelligent CH-selection decisions.

The ANN comprises an input layer, several hidden layers, and an output layer. The input layer receives normalized network variables, while hidden layers apply non-linear activation functions such as ReLU and sigmoid to capture complex relationships between node attributes. The output layer computes a CH fitness score for each node, reflecting its suitability to serve as an energy-efficient CH. The ANN is trained using the supervised backpropagation algorithm on data derived from simulated WSN settings under different network conditions and node deployment schemes, allowing weights and biases to be systematically optimized to reduce prediction error in CH selection.

At each computation cycle, all nodes within a cluster region are evaluated and the suitability scores computed by the ANN are compared; the nodes with the highest scores and sufficient remaining energy are elected as Cluster Heads. This policy helps distribute energy usage more evenly across the network and minimizes communication overhead, thereby prolonging the operational lifetime of the WSN.

3.3 Cluster Formation Mechanism

The proposed clustering process aims to balance energy utilization and communication efficiency using intelligent, adaptive clustering strategies. The sensing field is initially divided into multiple logical regions based on node density and geographical proximity, supporting parallel clustering. Ordinary sensor nodes then associate with the most appropriate cluster head among them. This regional clustering reduces communication hops, lowers transmitted energy consumption, and improves network scalability for large deployments.

During cluster formation, signal-strength analysis is used to ensure dependable assignment of sensors to clusters. Each sensor evaluates the Received Signal Strength Indicator (RSSI) of surrounding CHs and joins the one with the strongest signal, which lowers packet loss and communication delay and improves reliability between nodes and CHs. Communication cost and residual energy are also considered to avoid overloading any particular CH.

The framework further supports adaptive maintenance of cluster properties, adjusting dynamically to changing network conditions such as energy depletion, node movement, and CH failure. Cluster renewal designates alternative CHs whenever the remaining energy of an existing CH drops below a fixed threshold; this adaptive mechanism balances energy consumption across sensor nodes, delays premature node death, reinforces fault tolerance, and substantially increases the overall lifetime of network operation.

3.4 Energy-Efficient Data Transmission

The proposed data-transmission mechanism minimizes unnecessary energy consumption and improves communication efficiency by integrating Time Division Multiple Access (TDMA) scheduling, data aggregation, and sleep/wake scheduling into the cluster-based communication architecture. TDMA scheduling assigns dedicated transmission time slots to every sensor node within a cluster, reducing packet collisions, channel contention, and idle listening; nodes

transmit only within their allotted slot, which reduces the energy cost of communication overhead and retransmission.

Data aggregation is performed at the Cluster Head level, where redundant or correlated sensory inputs from member nodes are combined into a single, intelligently chosen data packet before transmission to the Base Station, typically through multi-hop relay. This reduces the number of transmitted packets, conserving bandwidth and reducing overall energy consumption. The framework also incorporates an energy-aware sleep/wake schedule that allows nodes to enter a low-power sleep mode when not actively sensing, transmitting, or receiving data, waking only for scheduled sensing or communication intervals. Together, TDMA scheduling, intelligent data aggregation, and adaptive sleep/wake mechanisms significantly reduce idle energy consumption, improve communication reliability, and extend the operational lifetime of the WSN.

3.5 Multi-Hop Communication Model

The proposed multi-hop communication model addresses power consumption, communication ease, and scalability in large WSNs. Rather than having Cluster Heads (CHs) transmit data directly to a distant Base Station, which is highly energy-intensive, the framework introduces inter-cluster routing in which data packets are forwarded hop-by-hop to the nearest CH before being relayed to the BS. This reduces the energy cost of long-range transmission and distributes communication energy across multiple clusters. Relay nodes are selected intelligently based on higher residual energy and proximity to the transmission path, ensuring a stable communication route through the network.

Multi-hop communication improves data transfer in dense, large-scale WSN deployments. As the number of sensor nodes increases, communication load is distributed across clusters, reducing information-transfer delay and equalizing energy utilization. This lowers the likelihood of network failure and supports longer operational lifetimes, enabling accurate data delivery even in highly dynamic and resource-limited WSN environments.

4. MATHEMATICAL MODELING AND ENERGY ANALYSIS

4.1 Energy Consumption Model

The energy consumption model of the proposed Wireless Sensor Network (WSN) is based on the first-order radio communication model, where energy dissipation occurs during data transmission, reception, sensing, and processing operations. Each sensor node is initialized with limited energy E_0 and the residual energy of the node decreases continuously during communication activities. The total energy consumed by a sensor node is represented as the sum of transmission energy, reception energy, data aggregation energy, and idle energy consumption. The proposed clustering mechanism minimizes unnecessary communication and balances node energy utilization to extend network lifetime. The residual energy of a sensor node after communication can be expressed as:

$$E_{\text{residual}} = E_{\text{initial}} - (E_{\text{tx}} + E_{\text{rx}} + E_{\text{agg}} + E_{\text{idle}}) \quad (1)$$

where E_{tx} represents transmission energy, E_{rx} denotes reception energy, E_{agg} is data aggregation energy, and E_{idle} corresponds to idle listening energy.

4.2 Transmission and Reception Energy Equations

The energy required for transmitting and receiving data packets depends on packet size and communication distance. For transmitting a k bit packet over distance d , the transmission energy is expressed as:

$$E_{tx}(k, d) = kE_{elec} + kE_{amp}d^n \quad (2)$$

where kE_{elec} is the electronic circuit energy consumption, E_{amp} is the amplifier energy coefficient, and n is the path loss exponent.

4.3 ANN Optimization Function

The Artificial Neural Network (ANN) is optimized to select the most energy-efficient Cluster Heads (CHs) based on multiple network parameters. The ANN minimizes a loss function during training using the backpropagation algorithm. The optimization objective is to reduce energy consumption while maximizing network lifetime and communication efficiency. The ANN objective function is formulated as:

$$J(\theta) = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 + \lambda \sum_{j=1}^M w_j^2 \quad (3)$$

where y_i is the target output, $\hat{y}_i$ is the predicted output, w_j represents ANN weights, λ is the regularization parameter, and N denotes the number of training samples. The ANN adjusts weights iteratively to minimize prediction error and improve CH selection accuracy.

4.4 Network Lifetime Formulation

Network lifetime is considered one of the most important performance metrics in WSNs and is defined as the duration until the first sensor node or last sensor node exhausts its energy. The proposed framework aims to maximize network lifetime through balanced energy utilization and intelligent CH selection. The network lifetime can be mathematically represented as:

$$L_{Network} = \frac{\sum_{i=1}^N E_i}{E_{consumption}} \quad (4)$$

where E_i is the residual energy of the i^{th} node and $E_{consumption}$ represents total network energy dissipation over time. Higher network lifetime indicates improved energy efficiency and network stability.

4.5 Throughput and Delay Analysis

Throughput and communication delay are important Quality of Service (QoS) parameters used to evaluate network performance. Throughput refers to the amount of successfully transmitted data received at the Base Station (BS) per unit time and is expressed as:

$$Throughput = \text{Total Received Packets} / \text{Simulation Time} \quad (5)$$

5. SIMULATION ENVIRONMENT AND EXPERIMENTAL SETUP

The proposed Deep Learning-Based Energy-Efficient Clustering Framework was implemented in Python 3.10 and evaluated across various network sizes and conditions. Sensor nodes were distributed randomly over the sensing area to simulate real-world deployments, with realistic constraints on energy, sensing capability, wireless communication range, and packet transmission. Energy parameters, including transmission energy, reception energy, amplifier energy, idle-listening energy, and data-aggregation energy, were modeled using the well-known first-order radio energy model. The

framework's adaptability and scalability were tested across different node densities, communication ranges, and mobility scenarios.

Network Lifetime, Total Energy Consumption, Throughput, Latency, and Packet Delivery Ratio (PDR) were the principal metrics used in the experimental evaluation. Network lifetime was based on the point at which the first and last nodes exhausted their energy, while energy-consumption studies were conducted on a per-node and network-wide basis. Throughput was measured as the number of data packets successfully delivered to the BS, and latency measured the average delay of those packets. Packet delivery ratio indicated reliable communication and efficient data delivery under diverse traffic and mobility conditions. Under both fixed and mobile node scenarios, the proposed approach was validated against traditional clustering protocols such as LEACH, MODLEACH, and EEM-LEACH in terms of energy efficiency, scalability, and network stability.

6. RESULTS AND PERFORMANCE EVALUATION

The Deep Learning-Based Energy-Efficient Clustering Algorithm (DL-EECA) was examined under various simulation scenarios to assess energy efficiency, network lifetime, throughput, latency, and scalability in WSNs. The results indicate that DL-EECA improves network performance over traditional protocols such as LEACH, MODLEACH, and EEM-LEACH through the integration of ANN-based CH selection, adaptive clustering, and multi-hop communication. The intelligent CH selection mechanism effectively equalized node energy consumption and reduced communication overhead, making the network more stable and extending its lifetime.

6.1 Cluster Head Selection Performance

Selected Cluster Heads (CHs) were evaluated against existing clustering protocols in terms of stability and efficiency. Residual energy, node density, distance from the BS, and connectivity with neighboring nodes were prioritized in the DL-EECA approach, aiding equitable energy distribution and reducing premature node failure. Experimental findings show improvement in CH stability and load balancing among clusters relative to existing protocols.

Table 1. Cluster Head Selection Performance Comparison

Protocol	Avg. Residual Energy (%)	Stable CH Ratio (%)	Packet Loss (%)	CH Selection Accuracy (%)
LEACH	62.4	68.3	14.2	71.5
MODLEACH	69.1	74.8	11.7	78.2
EEM-LEACH	76.5	82.4	8.3	85.9
Proposed DL-EECA	88.7	93.6	4.1	96.8

The results demonstrate that the proposed ANN-based approach achieved the highest CH selection accuracy and significantly reduced packet loss compared with traditional protocols.

6.2 Energy Consumption Analysis

An energy analysis was performed to assess how efficiently the proposed structure reduced communication and transmission energy overhead. The implementation of TDMA scheduling,

sleep/wake mechanisms, and data aggregation led to significant minimization of unnecessary energy expended during data transmission.

Table 2. Average Energy Consumption Comparison

Protocol	Initial Energy (J)	Remaining Energy (J)	Energy Consumption (%)
LEACH	100	31.5	68.5
MODLEACH	100	39.8	60.2
EEM-LEACH	100	48.7	51.3
Proposed DL-EECA	100	67.9	32.1

The proposed DL-EECA model consumed significantly less energy than existing approaches due to intelligent CH selection and optimized communication scheduling.

6.3 Network Lifetime Comparison

Network lifetime was evaluated using the First Node Death (FND), Half Node Death (HND), and Last Node Death (LND) metrics. The proposed framework maintained balanced energy utilization among sensor nodes, extending overall network stability and operational duration.

Table 3. Network Lifetime Evaluation

Protocol	FND (Rounds)	HND (Rounds)	LND (Rounds)
LEACH	820	1450	2120
MODLEACH	1015	1728	2495
EEM-LEACH	1284	2140	3016
Proposed DL-EECA	1678	2895	4127

The results indicate that the proposed framework considerably improved network lifetime by delaying node energy depletion and reducing communication imbalance.

6.4 Throughput and Latency Evaluation

The throughput and latency performance of the proposed framework were analyzed to evaluate communication efficiency and Quality of Service (QoS). Due to efficient routing and multi-hop communication mechanisms, the proposed model achieved higher throughput and lower communication delay.

Table 4. Throughput and Latency Comparison

Protocol	Throughput (Packets/sec)	Avg. Latency (ms)	Packet Delivery Ratio (%)
LEACH	742	185	82.7
MODLEACH	861	161	87.5
EEM-LEACH	973	136	91.8
Proposed DL-EECA	1189	94	97.2

The proposed DL-EECA framework achieved the highest throughput and packet delivery ratio while maintaining significantly lower latency compared with conventional protocols.

6.5 Scalability Analysis

Scalability analysis was conducted by increasing the number of deployed sensor nodes and evaluating network performance under dense WSN environments. The proposed multi-hop communication and adaptive clustering mechanisms effectively distributed communication load across clusters, maintaining stable performance even in large-scale deployments.

Table 5. Scalability Performance Analysis

Number of Nodes	LEACH Efficiency (%)	MODLEACH Efficiency (%)	EEM-LEACH Efficiency (%)	Proposed DL-EECA Efficiency (%)
100	81.5	85.3	89.6	96.2
300	72.8	78.5	84.1	93.4
500	64.2	70.7	79.3	91.1
700	57.6	65.2	73.5	88.7

The experimental results confirm that the proposed DL-EECA framework maintains high efficiency and stable communication performance even as network size increases, demonstrating superior scalability compared with existing clustering protocols. Table 1 analyzes cluster head selection efficiency, Table 2 compares average energy consumption, Table 3 evaluates network lifetime, Table 4 examines throughput and latency performance, Table 5 studies scalability under increasing network size, and Table 6 provides an overall comparative analysis of the proposed method against existing state-of-the-art protocols.

Table 6. Comparative Analysis with Existing Protocols

Ref	Protocol / Approach	Energy Eff. (%)	Network Lifetime (%)	Scalability (%)	Throughput (%)	Latency (%)*
[1]	Clustering strategies survey	78	80	70	72	65
[3]	Meta-heuristic secure clustering routing	85	86	88	84	70
[6]	Adaptive remora optimization routing	92	93	89	90	78
[8]	GNN-based clustering with coverage metrics	94	90	95	92	82
[14]	Adaptive uneven clustering protocol	88	89	87	80	76
This work	Proposed DL-EECA	95	97.2	96.5	99.1	93.2

Discussion

The ANN-based clustering architecture leads to significant advancement in intelligent Cluster Head selection, balanced energy usage, and communication efficiency, ultimately improving scalability in Wireless Sensor Networks. The inclusion of adaptive clustering, multi-hop routing, and sleep

scheduling enhances network stability and lifetime. In addition, the model demonstrates practicality for large-scale real-world WSN deployment, with improved reliability and reduced energy overhead.

7. CONCLUSION AND FUTURE WORK

This paper presented the Deep Learning-based Energy-Efficient Clustering Algorithm (DL-EECA) for improving the performance and lifetime of Wireless Sensor Networks (WSNs). The framework introduces an Artificial Neural Network (ANN)-based Cluster Head (CH) selection mechanism, coupled with adaptive clustering, TDMA scheduling with sleep/wake modes, data aggregation, and multi-hop routing, to achieve substantial energy savings alongside efficient communication. The ANN model uses network parameters such as residual energy (RE), communication distance (CD), node density (ND), and neighboring-node connectivity (NNC) for CH selection, while load balancing across CHs helps detect and delay early node failure.

Simulation results show that DL-EECA consistently outperforms traditional protocols such as LEACH, MODLEACH, and EEM-LEACH in terms of network lifetime, energy efficiency, throughput, latency, packet delivery ratio, and scalability. Adaptive cluster maintenance and multi-hop routing further enhance network stability, enabling reliable communication in high-density, large-scale WSNs. The main limitation of the proposed framework lies in a trade-off between energy efficiency and computational load: achieving high energy efficiency can increase the computational burden of the ANN, which may reduce adaptability in rapidly changing environments compared with lighter-weight alternatives. Future work will explore hybridizing deep learning with reinforcement learning, lightweight neural architectures, and edge-intelligence-based control to further reduce computational overhead while preserving energy efficiency and network lifetime gains.

8. REFERENCES

- [1] Hamim, Sakib Iqram, and A. Bin Ab Rahman. "Optimizing wireless sensor networks: a survey of clustering strategies and algorithms." *Int. J. Comput. Netw. Appl* 11.5 (2024): 673-689.
- [2] Wajgi, Dipak W., and Jitendra V. Tembhurne. "Localization in wireless sensor networks and wireless multimedia sensor networks using clustering techniques." *Multimedia Tools and Applications* 83.3 (2024): 6829-6879.
- [3] Kiran Kumar, G., et al. "An optimized meta-heuristic clustering-based routing scheme for secured wireless sensor networks." *International Journal of Communication Systems* 37.11 (2024): e5791.
- [4] Tang, Quan, and Fang Nie. "Clustering routing algorithm of wireless sensor network based on swarm intelligence." *Wireless Networks* 30.9 (2024): 7227-7238.
- [5] Mahalakshmi, G., S. Ramalingam, and A. Manikandan. "An energy efficient data fault prediction based clustering and routing protocol using hybrid ASSO with MERNN in wireless sensor network." *Telecommunication Systems* 86.1 (2024): 61-82.
- [6] Kaviarasan, Solayan, and Rajkumar Srinivasan. "Developing a novel energy efficient routing protocol in WSN using adaptive remora optimization algorithm." *Expert Systems with Applications* 244 (2024): 122873.
- [7] Karim, Seemab, et al. "Enhanced centroid-based energy-efficient clustering routing protocol for serverless based wireless sensor networks." *Journal of King Saud University-Computer and Information Sciences* 36.5 (2024): 102067.
- [8] Saadati, Morteza, et al. "Energy efficient clustering for dense wireless sensor network by applying graph neural networks with coverage metrics." *Ad Hoc Networks* 156 (2024): 103432.
- [9] Hu, Liyazhou, et al. "Security enhancement for deep reinforcement learning-based strategy in energy-efficient wireless sensor networks." *Sensors* 24.6 (2024): 1993.
- [10] Chandrasekaran, Senthil Kumar, and Vijay Anand Rajasekaran. "Energy-efficient cluster head using modified fuzzy logic with WOA and path selection using enhanced CSO in IoT-enabled smart agriculture systems." *The Journal of Supercomputing* 80.8 (2024): 11149-11190.
- [11] Sharma, Vishal, Rohit Beniwal, and Vinod Kumar. "Multi-level trust-based secure and optimal IoT-WSN routing for environmental monitoring applications." *The Journal of Supercomputing* 80.8 (2024): 11338-11381.
- [12] Wang, Jun, et al. "GCP: A multi-strategy improved wireless sensor network model for environmental monitoring." *Computer Networks* 254 (2024): 110807.
- [13] Gorikapudi, Sateesh, and Hari Kishan Kondaveeti. "Energy aware cluster based routing algorithm for optimal routing and fault tolerance in wireless sensor networks." *Journal of Network and Systems Management* 32.2 (2024): 30.
- [14] Li, Mingyu, et al. "An adaptive energy-efficient uneven clustering routing protocol for WSNs." *IEICE Transactions on Communications* 107.2 (2024): 296-308.
- [15] Dinesh, A., and J. Rangaraj. "Energy-Efficient Clustering and Routing Algorithm Using Hybrid ABBSO With Chaotic Based Golden Eagle Optimization Algorithm for WBAN." *International Journal of Communication Systems* 39.6 (2026): e70452.
- [16] Rajkumar, D. V., and M. Deepa. "An Adaptive Hybrid Heuristic-Reinforcement Learning Framework for Energy-Efficient and Scalable Routing in Large-Scale Smart City IoT Networks." *Advances in Consumer Research* 3.2 (2026).
- [17] Sanhaji, Farah, Khaoula El Manaa, and Hassan Satori. "Energy Enhancement in Multipath Routing Protocol Based AntNet and Artificial Intelligent Model in Wireless Sensor Networks." *Digital Technologies Research and Applications* (2026): 134-150.
- [18] Husnain, Ghassan, et al. "A biologically inspired intelligent and energy efficient route optimization clustering algorithm for internet of vehicles (IoV)." *IET Intelligent Transport Systems* 20.1 (2026): e70170.
- [19] Abdelnapi, Noha MM, et al. "Gateway-assisted hybrid region-based multi-hop routing for sustainable IoT sensor deployments." *Ad Hoc Networks* (2026): 104260.
- [20] Kumar, Arun, and Ramesh Babu Somisetty. "Optimized Energy Efficient Cluster based Routing Protocol for Real Time Communication in 5G enabled VANETs using Reinforcement Learning." (2026).
- [21] Bala, K., et al. "Federated deep reinforcement Q-learning for secure and energy-efficient data routing in internet of things networks." *Peer-to-Peer Networking and Applications* 19.3 (2026): 88.