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REGAL-Driven Hierarchical Graph Reinforcement Network for Stable and Energy-Efficient Communication in Wireless Sensor Networks

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Abstract

Wireless Sensor Networks (WSNs) deployed in large-scale monitoring environments frequently experience rapid energy depletion, unstable routing behaviour, uneven load distribution, and reduced communication lifetime due to inefficient cluster head selection and repeated re-clustering operations. Existing clustering approaches mainly rely on static optimization or probabilistic decision mechanisms that fail to capture temporal energy variations, neighbourhood dependency relationships, and adaptive long-term decision learning, which leads to poor scalability and premature node failures. To address these limitations, this research proposes a novel Hierarchical Graph Reinforcement Network (HGRN) framework that integrates Graph Neural Network (GNN)-based structural representation learning, Residual Energy Gradient Attention Layer (REGAL)-driven energy-aware embedding generation, Deep Reinforcement Learning (DRL)-based adaptive cluster head selection, and Energy-Adaptive Partridge Optimization Algorithm (EA-POA)-based cluster refinement for intelligent and stable communication management in large-scale WSNs. Initially, sensor nodes are organized into clusters and transformed into graph representations where neighbourhood interactions and communication dependencies are preserved through graph construction. Subsequently, REGAL computes temporal residual energy gradients and dynamically assigns adaptive attention weights to prioritize energy-stable nodes during feature aggregation. The generated energy-aware node embeddings are then provided to the DRL framework, where an adaptive policy network continuously learns optimal cluster head selection strategies based on residual energy, node density, communication distance, traffic load, and neighbourhood connectivity information. Furthermore, EA-POA performs energy-aware optimization refinement using adaptive partridge movement strategies, load balancing analysis, stability evaluation, and communication cost minimization to obtain highly reliable cluster head configurations. Experimental evaluation was conducted using 1000 sensor nodes deployed over a 100×100m sensing region across 10000 communication rounds. The proposed HGRN framework achieved a network lifetime of 10000 rounds, residual energy of 535 J, packet delivery ratio of 89.8%, throughput of 6350 packets, and communication delay of 198 ms while reducing overall energy consumption to 1915 J. In addition, the proposed framework attained a load balancing index of 0.95, cluster head stability index of 0.93, survivability index of 0.89, and successful packet transmission rate of 89.8%, thereby demonstrating superior communication stability, balanced energy utilization, reduced packet loss, and improved long-term network sustainability compared with existing clustering approaches.

Keywords; Deep Reinforcement Learning (DRL), Residual Energy Gradient Attention Layer (REGAL), Graph Neural Network (GNN), Energy-Adaptive Partridge Optimization Algorithm (EA-POA), Cluster Head Selection

1. Introduction

The Wireless Sensor Networks have turned out to be an integral part of IoT environments owing to its ability to sense, monitor, and transmit data in a distributed application environment such as healthcare, environment monitoring, industrial automation, military monitoring, disaster management, and smart cities [1]. But, because of the limited battery resources available at the sensor nodes, there is excess energy utilization, unstable communication, imbalanced workload distribution, and low network lifetime in the continuous operation of WSN [2]. Clustering techniques have been used for efficient communication and energy conservation where the role of Cluster Heads (CH) is to aggregate and transmit the sensed data to the sink node. Several optimization-based clustering techniques such as E-GLBR (Evolutionary Gateway-based Load Balanced Routing), integration of K-means and Firefly Algorithm (FA), AG-LEACH (Adaptive Grid Based LEACH), and Minimal Sensor Node Selection (MSNS) have been proposed [3][4].

Other recent studies have also concentrated on intelligent cluster head selection and optimization-based strategies for enhancing routing performance and the sustainability of WSNs in dynamic conditions [5]. The Stochastic Cluster Head Selection Model (SCHSM) made use of clustering by means of Genetic Algorithm (GA), along with movable sinks for optimized energy utilization and minimizing the burden on the network infrastructure. On the other hand, the Deep Learning-Hybrid Energy-Efficient Distributed (DL-HEED) strategy used Graph Neural Network (GNN) for intelligent clustering based on node topologies and their energy consumption capabilities [6][7]. For Software Defined Wireless Sensor Networks (SDWSNs), the DBlock-RLB model introduced blockchain in routing by means of Dual Agent-Twin Delayed Deep Deterministic Policy Gradient (DA-TD3) for secure routing strategies. Furthermore, the Optimized Energy-Efficient Knapsack Algorithm enhanced the process of cluster head selection based on optimization of residual energy and communication overheads [8] [9].

Some other intelligent techniques have been designed that consider incorporating intelligent learning and optimization techniques to achieve energy-efficient communication in WSNs. For instance, ensemble learning approach consisting of DNN, LSTM, and MLP models in combination with SOA was employed for improving secure routing and balancing energy load among various nodes in malicious communication environment [10]. Similarly, another algorithm called Improved LEACH along with FFA and ANN was implemented for achieving better cluster heads selection and secure routing via detecting malicious nodes and optimizing data communication routes. Besides, intelligent load balancing technique using GEO and Graph Neural Network and logistic regression (GNN-LR) can provide an efficient mechanism for balancing loads among different nodes for identifying malicious requests in cloud-supported WSN networks [11]. Despite some significant improvements in energy efficiency and performance metrics, all the above techniques suffer from several shortcomings in terms of capturing temporal energy dynamics, graph-based neighbourhood relations, and adaptive optimization for improving energy-efficient communication performance in WSN networks. Hence, the need for an intelligent and energy-aware cluster-head-based framework, which incorporates graph representation learning techniques as well as adaptive reinforcement learning techniques for cluster head improvement, is evident [12].

Rapid advancements in IoT infrastructures have resulted in a considerable need for WSN communication systems that are adaptive and energy efficient to sustain autonomous sensor operations for an extended period. Although several schemes of clustering and routing have been suggested to optimize network lifetime and stabilize communication, current WSN implementations continue to suffer from high energy imbalances, instability in cluster formation, high communication overhead, and early depletion of nodes owing to the presence of dynamic traffic and topology. In addition, today's sensor environments are characterized by constantly evolving interactions between nodes and energy dynamics that cannot be efficiently solved by traditional optimization techniques or heuristic-based clustering approaches. It was the need to deal with such problems that inspired researchers to come up

with an intelligent system that is capable of concurrently optimizing structural, communication, and energy decisions in WSNs.

Currently employed strategies for cluster formation within WSNs are solely focused on residual energy management, routing performance, or intelligent swarm-based techniques for choosing cluster heads without considering coordinated interaction among graph topology, time-dependent energy variations, and intelligent adaptive decisions. Many traditional optimization strategies depend on static mathematical formulations of fitness functions, which cannot adapt cluster heads according to changes in the dynamic behaviour of communication and energy consumption. Even though there have been some advancements by employing machine learning algorithms in recent years to enhance communication, such algorithms cannot consider temporal dependency of residual energy in neighbourhoods' aggregation, hence causing problems in terms of cluster head selection and frequent re-clustering of nodes.

- Proposed an innovative Hierarchical Graph Reinforcement Network (HGRN) architecture combining Graph Neural Network (GNN), Deep Reinforcement Learning (DRL) algorithms, and Energy-Adaptive Partridge Optimization Algorithm (EA-POA) to select energy-efficient cluster heads in Wireless Sensor Networks.
- Implemented the Residual Energy Gradient Attention Layer (REGAL) module to consider temporal residual energy analysis in graph neural networks to generate energy-stable node embedding for effective cluster head management.
- Proposed a DRL-based adaptive clustering framework that uses residual energy, node density, communication distance, traffic volume, neighbour connectivity, and REGAL generated node embedding to learn optimal cluster head policies over time.
- Proposed a clustering refinement framework based on EA-POA with adaptive partridge movement operations, cluster head stability improvement, communication overhead minimization, and load balancing analysis to increase the efficiency of clustering operations.

The performance of the designed HGRN was analysed through experiments conducted on a simulation model consisting of 1000 sensor nodes deployed in a 100×100m sensing environment by considering several wireless communication parameters like network lifetime, survivability, throughput, packet delivery ratio, energy efficiency, cluster head stability, computational complexity, and load balancing efficiency. The rest of the article is structured in the following manner. **Section 2** provides an overview of the previous literature on clustering techniques, routing schemes, and energy-efficient wireless communication mechanisms in WSNs. In **Section 3**, the design of the Hierarchical Graph Reinforcement Network (HGRN) is discussed, which involves graph representation, Residual Energy Gradient Attention Layer (REGAL), Deep Reinforcement Learning (DRL)-based selection of the cluster head, and Energy-Adaptive Partridge Optimization Algorithm (EA-POA). Finally, **Section 4** and **Section 5** describes the experimental evaluation based on different communication and energy parameters and concludes the research findings.

2. Related Works

Recently, researchers have dedicated a great deal of attention towards improving energy efficiency, routing reliability, and cluster head optimization within WSNs using intelligent clustering and adaptive optimization techniques. DBDQN-WGMO proposed an innovative method which incorporated the use of Deep Q-Network-based cluster head selection along with the Wild Geese Migration Optimization strategy for relay node selection and routing optimization. The scheme enhanced the packet delivery rate while minimizing the communication delay due to density-aware clustering and optimized routing. Similarly, the MSHDGP scheme used hierarchical clustering, ASZS load balancing technique, and dynamic buffer management for minimizing congestion and enhancing the efficiency of packet transmission in large-scale WSNs [13]. Moreover, the FHHO technique was based upon the combination of fuzzy logic and Harris Hawks Optimization which facilitated the

selection of cluster heads based upon their residual energy and communication distance parameters, leading to better throughput and operational stability of the WSNs [14][15]. Additionally, FK-meansRA was an adaptive clustering approach which utilized K-means clustering along with Mamdani Fuzzy Inference System (MFIS) for intelligent cluster head selection and load balancing within heterogeneous WSNs [16].

Some hybrid models were adopted in the cluster head selection algorithms to enhance communication efficiency and energy savings in wireless sensor networks. For instance, the Firefly and Cuckoo Search optimization protocol used node lifespan prediction and neighbourhood analysis of nodes to select the best cluster heads that can facilitate communication between the network nodes. Another hybrid approach involved the Markov Model and Artificial Bee Colony protocol, which was designed based on residual energy, buffer status, and node locations to perform cluster head selection and enhance the routing process [17][18]. On the other hand, the Innovative Dragonfly Algorithm incorporated the MADM decision-making framework with the dragonfly optimization algorithm for cluster head selection and considered the parameters of QoS, delay, energy, and load balancing within the network. The Improved Q-learning Artificial Bee Colony (IQ-ABC) model employed Q-learning algorithm together with artificial bee colony optimization and fuzzy logic techniques to balance routing exploration and exploitation and reduce latency and communication costs. Additionally, the dual path multiscale attention guided network with leaf in wind optimization algorithm DMAGN-CHS-WSN performed intelligent cluster head selection and efficient routing through multiscale feature analysis [19][20][21].

In addition, recent advancements have considered adaptive clustering along with energy-based optimization techniques for the sustenance and stability of clusters in IoT-based WSNs [22]. For instance, the CH-GWO protocol has considered residual energy, node coverage, and communication distance for cluster head optimization to ensure better network lifetime and scalability [23][24]. Like the approach, the BHOA-CM algorithm has used an adaptive mechanism for mutation and crossover techniques alongside a multi-objective approach for evaluating the fitness function for energy-based cluster head selection as well as effective communication handling. On the other hand, the Improved Snow Ablation Optimizer (ISAO) has been implemented to consider exploration and diversity conservation for cluster head optimization based on node density, energy consumption rate, and intra-cluster communication distances. Additionally, the RSA-IT2FLS algorithm has incorporated the trust factor and delay in addition to the residual energy while making decisions regarding cluster formations for secure routing and clustering. Furthermore, the ISSA-C algorithm has considered adaptive initialization of populations alongside step size adaptation in its implementation for energy-efficient clustering and routing. Finally, PGAECR has been proposed to perform clustering and routing optimizations simultaneously by combining both tasks into a single chromosome structure [25][26][27].

Several more sophisticated models that incorporate swarm intelligence, fuzzy logic, and adaptive mobility algorithms have been proposed to solve issues of energy imbalance and routing instability in the highly dynamic environment of WSNs. For instance, the Improved Salp Swarm and Bare Bones Mayfly Optimization Algorithm (ISSBBMFOA) used Improved Salp Swarm Optimization for selection of cluster heads while using Bare Bones Mayfly Optimization for handling sink mobility to increase throughput and ensure stable performance [28]. In turn, intelligent unequal clustering based on COA, fuzzy logic, and game-theoretic routing provided cluster formation as well as adaptive routing. Moreover, Multi-Objective Butterfly Clustering Optimization (MBCO) incorporated butterfly-based optimization, hybrid data fusion, and adaptive cross-cluster communication techniques to enhance cluster coordination capabilities. Furthermore, the EECHIGWO algorithm was used to select the most appropriate cluster heads considering their residual energy and distance to sinks [29].

Furthermore, MCSOC framework was used to extend energy-efficient clustering into EH-WSNs through energy-harvesting capabilities, inter-cluster cost, and sink distance consideration while forming clusters [30][31]. Moreover, the SA-RBM-SWHO approach incorporated smart task

scheduling and load balancing into cloud-assisted WSN-IoT networks using secure cluster head selection and hibernation-aware migration management strategy [32][33]. AbRBM enhanced overloaded communication management using Aquila optimization and radial basis neural model for efficient cluster head monitoring and communication balance. Finally, a KDE-based adaptive clustering approach involved silhouette-optimized K-means clustering, Bayesian cluster head selection, adaptive coverage, and CSMA/CA communication techniques to enhance energy conservation and cluster stability [34]. Although all these methods provided substantial enhancements in terms of energy conservation, throughput, and routing, most of the previous research is still lacking an effective means of handling temporal energy dynamics, graph learning of neighbourhood dependencies, and decision-making for efficient cluster head selection in highly dynamical WSN environments [35].

WSNs used for massive sensory operations face major challenges because of their continuous energy loss, communication instability, cluster head overload, and ineffective route control among the dispersed sensors. Cluster heads in WSNs often face the challenge of heavy communication loads since the current clustering algorithms fail to dynamically balance loads depending on the energy levels and communication activities within the vicinity of the nodes. This results in fast depletion of energy, failed communication of packets, higher latencies, and less survival of the network, which have an impact on the performance and sustainability of the WSN communication framework. Additionally, current clustering strategies and conventional optimizations fail to adjust to the dynamic topology changes.

The other significant issue emanates from the incapacity of the currently used clustering paradigms to concurrently incorporate the dependencies between the nodes in terms of structure, energy evolution with time, and adaptive routing capabilities in the selection process of the cluster head. In most cases, such processes are done separately, leading to disjointedness in decision making that affects the communication efficiency of the network. Moreover, reformation of clusters due to unstable cluster head transitions becomes a source of added inefficiencies in both the communication and computation within the network, especially when sensors are densely deployed. This brings about the need for an intelligent clustering paradigm that incorporates feature representation through graphs, temporal energy-aware attention learning, reinforcement learning in selecting cluster heads, and optimization to enhance network stability.

3. Methodology

3.1 Overall Architecture of the Proposed HGRN Framework

The proposed Hierarchical Graph Reinforcement Network (HGRN) structure proposes a smart and energy-efficient clustering approach for a large scale WSNs through the combination of graph learning representation with intelligent optimization. In contrast to traditional clustering approaches, which primarily rely upon deterministic probabilistic selection and routing behaviour, the proposed system analyses the operational status of the sensors via deep structural learning as well as long-term policy optimization. An innovative aspect of the proposed system relates to the implementation of the Residual Energy Gradient Attention Layer (REGAL), which ensures that the Graph Neural Network (GNN) focuses on those sensors whose energy consumption is stable, while excluding nodes that experience rapid energy loss. Furthermore, Deep Reinforcement Learning (DRL) is applied to identify cluster heads through the continuous analysis of optimal policies learned through network interaction, whereas the Energy-Adaptive Partridge Optimization Algorithm (EA-POA) selects cluster heads taking into consideration their energy stability, communication costs, and balancing of load factors.

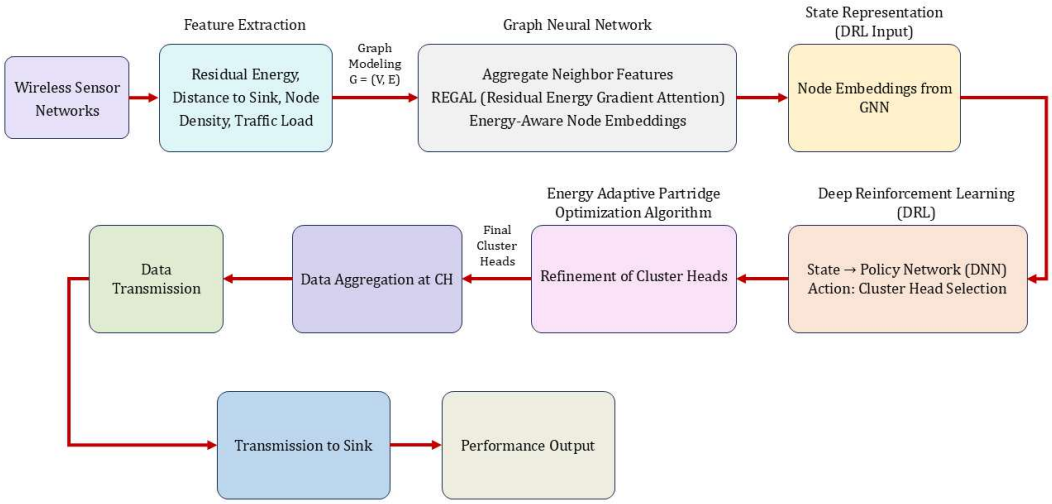


Figure 1. Overall Architecture of the Proposed HGRN Framework

The overall workflow of the designed HGRN architecture is visualized in Figure 1. First, sensing devices are deployed in the sensing region, after which the clustering process starts based on communication proximity and neighbouring nodes. In the post-clustering process, essential parameters for the nodes, including remaining energy, distance from the sink node, node density, and traffic load, are obtained to describe the present network situation. The above-mentioned parameters will then be employed to construct a graph structure of WSN, where each individual node in the graph is a sensor node while each link in the graph is the communication channel. The generated graph will then be fed into the enhanced GNN (REGAL), and the obtained node embeddings with the incorporation of long-term energy information and graph topology information will be used to train the DRL policy network, whose main function is to discover cluster head candidates that have better long-term reward results from the balance of energy expenditure and communications efficiency. After cluster head optimization, the information received by the sensor nodes is merged by the cluster heads to avoid repeated sending and reduce the communication cost by transmitting the information towards the sink node in a compressed form. Moreover, adaptive mechanisms for monitoring the load and energy level of the network ensure that any clustering process will take place in case of imbalances or high energy depletion within the network. As can be seen in Figure 1, this process leads to optimized resource usage and effective communication in the WSN.

3.2 Network Model and Assumptions

The Hierarchical Graph Reinforcement Network (HGRN) model proposed in this paper takes into consideration a Wireless Sensor Network (WSN) consisting of N sensor sensors that are randomly distributed in a two-dimensional sensing area of dimension A × A. Every sensor has the capability to sense, process, and transmit data wirelessly, but with limited battery power. These sensors constantly keep track of environmental conditions and pass on this data to an external sink. The set of all sensors can be written as:

$$S = \{s_1, s_2, s_3, \dots, s_N\} \tag{1}$$

where $s_i$denotes the i^{th}sensor node in the network. The sink node is represented as $BS(x_{bs}, y_{bs})$, while the position of each sensor node is defined by its coordinate pair (x_i, y_i). The Euclidean distance between two nodes $i$and $j$is calculated as:

$$d(i,j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{2}$$

Similarly, the distance between a sensor node and the sink node is expressed as:

$$d(i, BS) = \sqrt{(x_i - x_{bs})^2 + (y_i - y_{bs})^2} \quad (3)$$

Sensor nodes are always fixed after deployment, while sink nodes can either be static or mobile based on the application needs. All the nodes begin with equal energy levels denoted by E_0. Communication within the network is symmetrical; that is, the transmission parameters between any two nodes are the same for both directions of communication. All the nodes periodically exchange control data with other nodes within a communication range R_c. Two nodes are said to be neighbours if the following is true:

$$d(i, j) \leq R_c \quad (4)$$

Based on neighbourhood relationships, the WSN topology is transformed into a graph structure represented by:

$$G = (V, E) \quad (5)$$

where Vcorresponds to the collection of sensor nodes and Erepresents the communication links established among neighbouring nodes. This graph representation enables the proposed GNN framework to capture both local and global structural dependencies existing within the sensor network. The proposed energy model for wireless energy consumption uses a first-order radio energy model, which computes the cost of transmission and reception of a packet by the network. For transmission, a sensor node uses power for operating the transmitter hardware, and for amplifying signals. The amount of energy needed to transmit a k-bit message across a distance dis mathematically modelled as:

$$E_{TX}(k, d) = \begin{cases} kE_{elec} + k\epsilon_{fs}d^2, & d < d_0 \\ kE_{elec} + k\epsilon_{mp}d^4, & d \geq d_0 \end{cases} \quad (6)$$

Where, E_{elec}denotes the electronic circuitry energy consumption per bit, ϵ_{fs}represents the free-space amplifier coefficient, ϵ_{mp}indicates the multipath fading amplifier coefficient, and $d_0$is the threshold distance separating free-space and multipath propagation models. When the communication distance is smaller than d_0, the free-space propagation model is applied, resulting in energy dissipation proportional to d^2. Conversely, for larger communication distances, the multipath fading model is utilized, where energy consumption increases proportionally to d^4. This distinction enables realistic modeling of communication overhead in large-scale WSN environments.

Similarly, the energy consumed during packet reception depends only on the receiver electronics and is calculated as:

$$E_{RX}(k) = kE_{elec} \quad (7)$$

In addition to communication energy, cluster heads consume supplementary energy during data aggregation operations due to packet compression and redundant information elimination. The aggregation energy for a k-bit packet is represented as:

$$E_{DA}(k) = kE_{agg} \quad (8)$$

where E_{agg}denotes the aggregation cost per transmitted bit. The residual energy available at a sensor node after each communication round is subsequently updated according to:

$$E_i^{residual} = E_i^{current} - (E_{TX} + E_{RX} + E_{DA}) \quad (9)$$

The information obtained from the remaining energy becomes very useful for the REGAL-based feature learning approach and DRL-driven cluster head selection method being designed. With the use of realistic communication assumptions, graph-based topography, and the energy consumed by radios, the model of WSN developed herein forms a dynamic and energy-aware basis for intelligent clustering and transmission of data.

3.3 Cluster Formation and Feature Extraction

The processing stage of the suggested Hierarchical Graph Reinforcement Network (HGRN) framework includes grouping of sensor nodes in clusters in such a way as to facilitate efficient communication, as well as feature extraction at the node level, which will later be used for the intelligent election of the cluster head. Because large scale WSNs include multiple sensor nodes which are in different energy states and use diverse communication schemes, direct communication with the sink results in heavy energy consumption and inefficient network operation. Therefore, the first step in the proposed framework involves clustering as the means of creating localized communication infrastructure. Next, several energy-dependent and topology-dependent features are estimated for each individual sensor node. These are used later in REGAL-empowered GNN and DRL-based modules.

3.3.1 Initial Cluster Formation

In the initial phase of network operation, all sensor nodes transmit control packets to find neighbour nodes and build connectivity information locally. This allows all the nodes to find their neighbouring nodes within the transmission range defined in the network. Let $R_c$represent the communication range of a sensor node. Two nodes $s_i$and $s_j$are considered neighbors when the following condition is satisfied:

$$d(i,j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{10}$$

After discovering their neighbourhood, the sensor nodes are clustered depending on communication proximity and distribution of neighbouring nodes. Nodes that have closer distances are clustered together to ensure that the communication costs within the same cluster are minimized. Assume that C_m represents the m^{th} cluster within the network, which is defined as:

$$C_m = \{s_1, s_2, s_3, \dots, s_k\} \tag{11}$$

where $k$represents the number of member nodes belonging to cluster C_m. The cluster formation mechanism attempts to maintain balanced cluster sizes to avoid excessive traffic concentration on specific regions of the network. During neighbour discovery, an adjacency matrix is constructed to represent communication relationships among sensor nodes. The adjacency relationship between nodes is mathematically defined as:

$$A(i,j) = \begin{cases} 1, & d(i,j) \le R_c \\ 0, & otherwise \end{cases} \tag{12}$$

where $A(i,j) = 1$indicates the existence of a communication link between nodes $i$and j, while $A(i,j) = 0$denotes the absence of direct connectivity. This adjacency information is later utilized for graph construction and neighbourhood feature aggregation within the proposed GNN framework.

The distance-based approach to clustering helps reduce the long-distance communication burden considerably as the normal nodes in the network are required to communicate only with the cluster heads and not directly send data to the base station. As a result of this scheme for clustering, it is possible to achieve improved scalability and energy efficiency.

3.3.2 Node Feature Extraction

Once clusters have been formed, it is envisaged that the framework would be used to extract several features at the node level, which would give information about the energy status, communication capability, and importance in terms of topology of each sensor node.

(i) Residual Energy

The residual energy is the leftover energy in the battery of the sensor node after the communication and processing tasks. Because the cluster heads require extra energy for data

aggregation and transmission, those with high residual energy are better suited to be cluster heads. The residual energy of node *i* is defined as:

$$RE_i = E_i^{current} - E_i^{consumed} \quad (13)$$

Where, $E_i^{current}$ denotes the present energy level of node i, $E_i^{consumed}$ indicates the total energy utilized during communication and computation.

Cluster heads having more residual energy will be able to handle their duties for a longer time, leading to less node failure. Therefore, the recommended framework favours energy-rich nodes when selecting cluster heads.

(ii) Distance to Sink

The distance between the sensor node and the sink node affects the cost of communication and the energy spent during transmission. The further away a node is from the sink, the higher the transmission power it uses. The distance between the sink and node *i* is computed as:

$$DS_i = \sqrt{(x_i - x_{bs})^2 + (y_i - y_{bs})^2} \quad (14)$$

Where, (x_i, y_i) denotes the coordinate position of node i, (x_{bs}, y_{bs}) represents the sink node location.

Nodes located closer to the sink tend to use less power while communicating over greater distances and are therefore better choices for being selected as cluster heads. By taking sink distance into consideration while selecting features, the suggested approach would be able to minimize overhead and delay.

(iii) Node Density

Node Density is the measure of the density of neighbouring nodes around the sensor node in its communication range. Node density that is high shows better connectivity as well as good communication accessibility. Density of node *i* is determined by:

$$ND_i = \sum_{j=1}^{N} A(i,j) \quad (15)$$

Where, $A(i,j)$ represents the adjacency relationship between nodes i and j, N denotes the total number of nodes in the network.

The nodes that are denser will be able to communicate effectively amongst each other since they have better connectivity with their neighbouring sensor nodes. Hence, node density has been included in the process of choosing the cluster heads.

(iv) Traffic Load

Traffic load refers to the amount of traffic processed by the node while performing data transmission activities. Too much traffic processing by some nodes can lead to exhaustion of their battery and cause communication traffic congestion. The traffic load in relation to node *i* is defined as:

$$TL_i = \sum_{p=1}^{M} D_p \quad (16)$$

Where, D_p denotes the size of the p^{th} transmitted data packet, and M represents the total number of packets processed by node i.

Those nodes that have lesser traffic should be preferred while assigning the role of cluster heads since they will be able to manage extra communication tasks without getting exhausted. Incorporating traffic-related data into the feature extraction process helps attain better load balancing and reduces congestion.

(v) Neighbour Connectivity

Node neighbour connectivity refers to the strength of the interaction that exists between a node and the surrounding neighbours. Nodes which are highly connected have high routing flexibility capabilities and can sustain reliable communication channels in dynamic networks. The degree of connectivity of node *i is* given by:

$$NC_i = \frac{\sum_{j=1}^{N} A(i,j)}{N} \tag{17}$$

Where, $A(i,j)$indicates the existence of a communication link, Ndenotes the total number of sensor nodes.

High levels of connectivity increase the chances of stable connectivity while decreasing the possibility of occurrence of isolated clusters. It follows that nodes having high neighbour connectivity form favourable options for cluster heads in the suggested clustering algorithm. The feature vectors obtained thus provide information regarding energy attributes, communication efficiency, topological aspects, and workload balancing within the WSN network. Such multi-dimensional node representation vectors are used in the REGAL Graph Neural Network model to create energy-aware cluster head embedding vectors.

3.4 Graph Construction and GNN Modelling

The proposed Hierarchical Graph Reinforcement Network (HGRN) approach converts the WSN into a structured graph representation to effectively represent the relationships between communications, neighbourhoods, and energies of the nodes. Traditional clustering techniques tend to consider nodes individually, resulting in a lack of maintenance of topological structure amongst large networks of sensor nodes. To deal with this issue, the proposed approach represents WSN in the form of a graph, wherein node interaction is shown via communication edges. This graph representation allows the Graph Neural Network (GNN) to capture spatial relationships, neighbourhood relationships, and energy-based structural attributes needed for smart cluster head selection.

3.4.1 Graph Representation of WSN

The structure of each sensor node within the sensing region can be described using a graph vertex, and their communication relation is described as an edge. Assume that the graph representation of the WSN architecture is:

$$G = (V, E) \tag{18}$$

Where, $V = \{v_1, v_2, v_3, \dots, v_N\}$denotes the collection of graph vertices corresponding to sensor nodes, Erepresents the communication links established among neighbouring nodes.

Each sensor node keeps track of its connection details with other nodes which lie in the predetermined range R_c. The distance between nodes is calculated based on the formula:

$$d(i,j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{19}$$

To model the network connectivity formally, an adjacency matrix A is formed. The adjacency criteria between two nodes is established mathematically by:

$$A_{ij} = \begin{cases} 1, & d(i,j) < R_c \\ 0, & otherwise \end{cases} \tag{20}$$

Where, $A_{ij} = 1$indicates that nodes $i$and $j$are directly connected, $A_{ij} = 0$indicates the absence of direct communication. The adjacency matrix gives information about neighbourhoods of the nodes and network topology. Through the adjacency matrix, the proposed GNN architecture can aggregate

information from neighbouring sensor nodes during the process of feature extraction. The neighbourhood set of nodes i is given by:

$$N(i) = \{j \in V \mid A_{ij} = 1\} \tag{21}$$

where $N(i)$contains all neighbouring nodes connected to node i. Neighbourhood data plays a vital role since nodes placed inside the dense areas have higher connectivity and better reliability than those that are isolated. For the identification of the nodes inside the graph, various parameters of the network are used to represent the nodes. Representation of the feature vector of node I is denoted by:

$$X_i = [RE_i, DS_i, ND_i, TL_i, NC_i] \tag{22}$$

Where, RE_idenotes residual energy, DS_irepresents distance to sink, ND_iindicates node density, TL_icorresponds to traffic load, and NC_irepresents neighbor connectivity.

This graph-based approach will facilitate the suggested architecture in capturing both local and global topological structures in the WSN environment, hence promoting intelligent and adaptive clustering operations. As can be observed from Figure 2 below, the created graph structure provides an opportunity for neighbouring sensor nodes to communicate about their features using communication edges.

3.4.2 Graph Neural Network for Feature Learning

Following the graph construction stage, the energy awareness-based representation is learned using the Graph Neural Network, which captures structural information as well as neighbourhood information from the connected sensor nodes. This approach differentiates itself from traditional machine learning approaches that deal with individual node processing. The information transfer between nodes in the graph is continuous through the graph edges, allowing the learning algorithm to learn the interdependencies existing in the network.

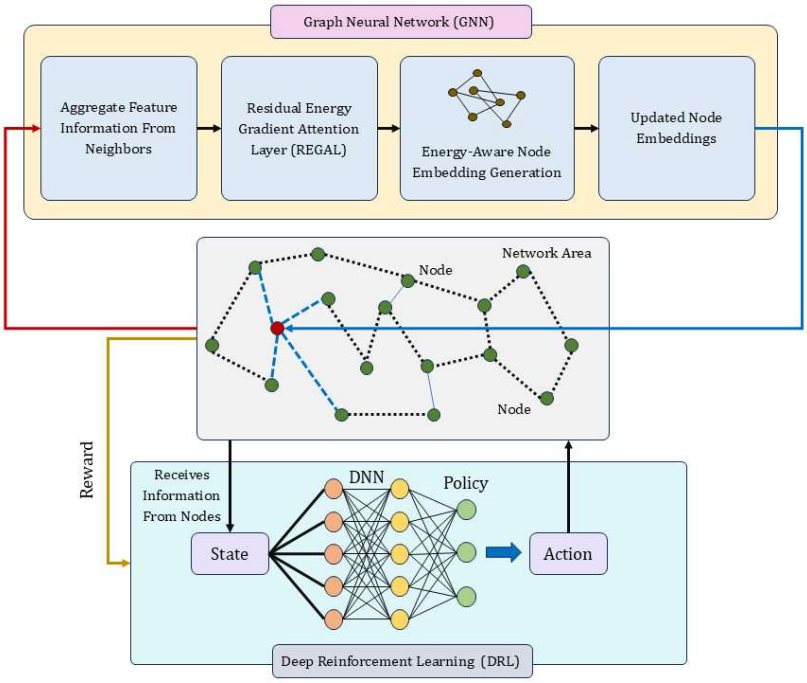


Figure 2. Graph Construction and GNN-Based Energy-Aware Feature Learning in the Proposed HGRN Framework

At the stage of message passing, each sensor node gathers the information about the features of its neighbours based on their adjacency matrix. Neighbourhood aggregation refers to an operation that helps to aggregate neighbouring node representations to provide enriched structural information. It can be represented as:

$$M_i^{(l)} = \sum_{j \in N(i)} A_{ij} H_j^{(l)} \tag{23}$$

Where, $M_i^{(l)}$denotes the aggregated message at layer l, $H_j^{(l)}$represents the hidden embedding of neighbouring node j, and A_{ij}defines the adjacency relationship between nodes. After neighbourhood aggregation, the resultant feature vector passes through learnable weight matrices along with nonlinear activation functions to create updated embeddings for the nodes. The propagation step carried out by the GNN proposed is expressed by:

$$H^{(l+1)} = \sigma(\hat{A}H^{(l)}W^{(l)}) \tag{24}$$

Where, $H^{(l)}$denotes node representations at layer l, $H^{(l+1)}$represents updated node embeddings, $\hat{A}$is the normalized adjacency matrix, $W^{(l)}$indicates the trainable weight matrix, and $\sigma(\cdot)$represents the nonlinear activation function.

The normalized adjacency matrix is computed as:

$$\hat{A} = D^{-\frac{1}{2}}(A + I)D^{-\frac{1}{2}} \tag{25}$$

Where, Drepresents the degree matrix, Idenotes the identity matrix used for self-loop incorporation. Self-loop aggregation makes sure that each node retains its feature information in the process of aggregation. Therefore, the new embeddings hold information not only about the local node but also about the structures in its neighbourhood. To further enhance the energy awareness capability of the system, the framework incorporates the Residual Energy Gradient Attention Layer (REGAL) in the Graph Neural Network. This layer focuses on the nodes having steady energy consumption patterns, downplaying the impact of nodes whose energy is fast draining off. As depicted in Figure 2, the GNN initially aggregates the neighbours' information, after which REGAL attention is applied for creating energy aware embeddings. The final node embedding generated after multiple GNN propagation layers is represented as:

$$Z_i = H_i^{(L)} \tag{26}$$

Where, $Z_i$denotes the final embedding of node i, and Lrepresents the total number of GNN layers. These embedding models learn the topological structure of communication, neighbourhood dependency, residual energy behaviour, and traffic flow distribution properties in the WSN. This leads to the GNN model being able to generate very informative representations that help make intelligent decisions regarding cluster head identification, optimal energy usage, and routing.

3.5 REGAL: Residual Energy Gradient Attention Layer

The Residual Energy Gradient Attention Layer (REGAL) represents one of the key innovations in the designed Hierarchical Graph Reinforcement Network (HGRN). Specifically, REGAL was developed for increasing the efficiency of Graph Neural Networks (GNNs) by considering the temporal energy dynamics in the process of node representations learning. While traditional GNN models are focused on using node structural topology and neighbourhood aggregations for feature propagations, no attention was paid to the speed of change in residual energy values of nodes over time. In such a situation, even those nodes that undergo battery drain very quickly can be assigned a significant value of embedding importance because of having a well-located position within the graph structure or due to highly connected positions. This way, cluster heads will not be selected properly, and network will experience faster fragmentation. To address this problem, the introduced REGAL model considers temporal dynamics of residual energy in the form of energy-aware attention and uses it for feature aggregations. The whole process of REGAL operation is presented in Figure 3.

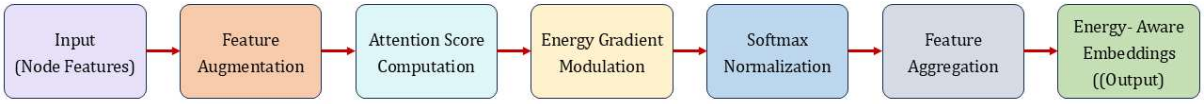


Figure 3. Overall Flow of the Proposed Residual Energy Gradient Attention Layer (REGAL)

Graph Neural Network-based methods concentrate only on the topology of relations among nodes and do not consider temporal variations of energy levels that may happen in the Wireless Sensor Network. While structurally motivated aggregation helps to capture information about neighbourhoods more accurately, the lack of consideration for energy-based weights might cause selection of nodes experiencing energy drainage. Since cluster head nodes perform data collection and packet forwarding operations, in comparison with normal sensors, their energy usage is much higher. Hence, choosing nodes with unstable energy behaviour as cluster heads might lead to their fast failure and increase packet drop rate.

In order to tackle this problem, a new REGAL mechanism has been designed which utilizes a temporal energy-aware approach, where the residual energy along with the energy change of a sensor node during different communication rounds is considered before allocating feature propagation weights to them. Sensor nodes having constant residual energy change during communication rounds receive higher attention importance weights, while those with sudden decrease in residual energy values receive less importance weight. The resultant GNN can create energy-sensitive node embeddings for accurate cluster head selection. The temporal energy variation of a node can be measured using differences between consecutive communication rounds. Those nodes having lower changes in residual energies are considered more stable than others and fit for being a cluster head, while those with higher negative changes denote greater energy drainages. As a result, the REGAL approach helps in achieving a more stable network through incorporating the temporal energy behaviour into GNN-based feature learning, as illustrated in Figure 3.

3.5.1 Energy Gradient Computation

Firstly, the energy gradient for every sensor node is determined during the initial phase of the REGAL technique. The energy gradient is basically the difference in residual energy for each time interval of communication and acts as a measure of node stability. The main advantage of determining the energy gradient of the nodes over their actual energy is that it enables the technique to differentiate temporary high-energy nodes from stable nodes.

The energy gradient of node $i$at communication round $t$is computed as:

$$\Delta E_i = E_i(t) - E_i(t-1) \tag{27}$$

Where, $E_i(t)$represents the current residual energy of node i, and $E_i(t-1)$denotes the residual energy during the previous communication round. A larger value of ΔE_i in negative indicates faster consumption of energy, while smaller values show that there is a constant behaviour of energy. The normalized energy gradient, to keep a check on energy fluctuation during attention learning, is given by:

$$\widetilde{\Delta E_i} = \frac{\Delta E_i - \Delta E_{min}}{\Delta E_{max} - \Delta E_{min}} \tag{28}$$

Where, $\Delta E_{min}$and ΔE_{max}denote the minimum and maximum energy gradient values observed within the network. After this normalization of the energy gradient, it is then integrated with the node features during attention calculations. This helps the suggested model achieve continuous evaluation of the energy usage pattern and elimination of nodes with erratic patterns of energy consumption. For quantification of energy stability, the energy stability coefficient is defined as:

$$S_i = \frac{1}{1+|\Delta E_i|} \tag{29}$$

Where, $S_i$denotes the stability score of nodes i. The nodes that experience low variations in terms of their energies exhibit high stability coefficients and, hence, become more significant in neighbourhood aggregation. The proposed energy-sensitive learning approach enhances the robustness of cluster head election within dynamic networks. The gradient values of the energies are incorporated into the REGAL attention mechanism prior to feature aggregation, as shown in Figure 3.

3.5.2 Attention Weight Computation

Following the computation of energy gradients, the new REGAL algorithm computes adaptive attention coefficients for neighbouring sensor nodes. The aim of this phase is to provide more significance to those sensors which have stable residual energy attributes, thus minimizing the contribution of sensor nodes with highly depleting batteries. While traditional graph-based attention algorithms rely heavily on features' similarities, the new REGAL module considers energy fluctuations during its attention learning process.

Let $h_i$and $h_j$denote the hidden feature representations of nodes $i$and j, respectively. The unnormalized attention score between neighbouring nodes is computed as:

$$e_{ij} = f(h_i, h_j, \Delta E_j) \tag{30}$$

Where, $f(\cdot)$represents the learnable attention function, and ΔE_jdenotes the energy gradient associated with neighbouring node j. The attention function incorporates both structural similarity and energy stability information. To penalize unstable nodes, the energy gradient is integrated into the attention computation using:

$$e_{ij} = a^T[Wh_i \;||\; Wh_j \;||\; \Delta E_j] \tag{31}$$

Where, Wdenotes the trainable transformation matrix, a^Trepresents the learnable attention vector, and ||indicates vector concatenation. The attention coefficients are normalized using the softmax function to ensure that the contributions of neighbouring nodes sum to unity. The normalized attention weight is calculated as:

$$\alpha_{ij} = \frac{\exp\left(f(h_i, h_j, \Delta E_j)\right)}{\sum_{k \in N(i)} \exp\left(f(h_i, h_k, \Delta E_k)\right)} \tag{32}$$

Where, α_{ij}denotes the normalized attention coefficient, and $N(i)$represents the neighbourhood set of nodes i.

The attention weights of nodes which have constant energy are also high because such nodes play an important role in contributing towards neighbourhood features. However, loss of energy by certain nodes causes attention weights of such nodes to be low. Energy aware embedding for each node *i* is formed through aggregation of neighbour node representations using computed attention weights:

$$h_i{}' = \sigma\left(\sum_{j \in N(i)} \alpha_{ij} W h_j\right) \tag{33}$$

Where, h_i'denotes the updated node embedding, and $\sigma(\cdot)$represents the nonlinear activation function.

By employing such an adaptive attention technique, the presented REGAL layer successfully exploits the temporal dynamics of energy while ensuring neighbourhood structure integrity. Thus, the resulting node embedding becomes extremely valuable for Deep Reinforcement Learning-based cluster head selection.

3.5.3 Energy-Aware Node Embedding

After computing attention weights, the proposed REGAL layer uses neighbourhood aggregation with weights to form energy-aware node embeddings incorporating both graph structure and energy

dynamics on the graph. In contrast to traditional GNN embeddings, which only consider structural relations, the proposed embeddings also consider the energy stability of nodes in addition to their structure.

The energy-aware embedding associated with node $i$is generated using:

$$z_i = \sigma\left(\sum_{j \in N(i)} \hat{\alpha}_{ij} W h_j\right) \tag{34}$$

Where, $z_i$denotes the final energy-aware embedding, $\hat{\alpha}_{ij}$represents the REGAL-based attention coefficient, $W$is the trainable weight matrix, and $\sigma(\cdot)$indicates the nonlinear activation function. The embedding vectors are rich with respect to the residual energy condition, neighbourhood connectivity, communication topology, traffic behaviour, and energy stability at different time instances. Figure 3 shows how REGAL executes feature enhancement, attention calculation, energy gradient adjustment, SoftMax normalization, and finally feature combination in sequence before producing energy-aware embeddings for the nodes. The resultant embeddings are then used as inputs for the Deep Reinforcement Learning (DRL) module, which learns adaptive strategies for choosing appropriate cluster heads by optimizing the wireless sensor network from the perspective of maximizing its overall longevity. Through the incorporation of temporal energy awareness into graph attention networks, REGAL offers substantial improvements in terms of clustering stability, avoidance of early node failures, communication costs, and network lifespan.

3.6 DRL-Based Adaptive Cluster Head Selection

The designed Hierarchical Graph Reinforcement Network (HGRN) framework makes use of the Deep Reinforcement Learning (DRL) approach in order to adaptively select energy-aware cluster heads in Wireless Sensor Networks. Conventional approaches for cluster head selection normally utilize fixed threshold values, probability-based models, and rules-based frameworks that lack the capability to dynamically adapt to changes in the state of the network, including unequal energy dissipation, traffic load balancing issues, and topology dynamics. In doing so, the continuous selection of suboptimal cluster heads leads to inefficient communications, fast node depletion, and poor scalability of the network. The HGRN framework uses the REGAL-based energy-aware node representation and reinforcement learning to enable intelligent cluster head selection by optimizing rewards and interacting continuously with the wireless sensor environment.

3.6.1 Reinforcement Learning Environment

The suggested framework of reinforcement learning considers the problem of cluster head selection as a decision-making process whereby an intelligent learning agent keeps on interacting with the environment of wireless sensor network. At each communication time-step, the learning agent perceives the current state of the network, makes cluster head selections, and gets rewards based on the quality of cluster selection.

In the suggested environment model, the wireless sensor network is considered as the environment Env and the reinforcement learning controller as the learning agent Ag. Prior to taking any action, the agent perceives information such as residual energy of the nodes, communication distance between nodes, density of nodes, traffic flow, and REGAL generated node embeddings.

The interaction between the agent and environment can be represented as:

$$Env = \{S, A, R, P\} \tag{35}$$

Where, Sdenotes the state space, Arepresents the action space, Rindicates the reward function, and Pdefines the state transition probability.

In each communication round t, the agent gets state S_t of the network, acts A_t, and gets the reward R_t. Then the environment transitions to the next state $S_{(t+1)}$ based on the selected cluster head arrangement. The goal for the DRL agent is to maximize the overall reward given by:

$$G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k} \tag{36}$$

Where, $G_t$denotes cumulative future reward, γrepresents the discount factor, and R_{t+k}indicates future rewards obtained after $k$communication rounds. This learning strategy enables the proposed framework to avoid short-sighted decisions and instead select cluster heads that improve long-term network lifetime and communication efficiency.

3.6.2 State Representation

The efficiency of reinforcement learning largely depends upon the quality of state representation observed. Hence, the framework of the proposed HGRN algorithm incorporates a detailed state vector with the incorporation of network topology and energy features into consideration. The state information fed to the DRL algorithm includes residual energy, distance for communication, node density, traffic load, and REGAL-based energy embeddings.

The state representation corresponding to node $i$is expressed as:

$$S_i = [RE_i, DS_i, ND_i, TL_i, Z_i] \tag{37}$$

where, RE_idenotes residual energy, DS_irepresents distance to sink, ND_iindicates node density, TL_icorresponds to traffic load, and $Z_i$represents the REGAL-generated embedding vector.

The residual energy component is represented as:

$$RE_i = E_i^{current} - E_i^{consumed} \tag{38}$$

which reflects the remaining operational capability of the sensor node.

The distance-to-sink parameter is calculated using:

$$DS_i = \sqrt{(x_i - x_{bs})^2 + (y_i - y_{bs})^2} \tag{39}$$

Where, (x_i, y_i)denotes node coordinates, (x_{bs}, y_{bs})indicates sink node position.

The node density information is computed as:

$$ND_i = \sum_{j=1}^{N} A(i,j) \tag{40}$$

which measures the local connectivity strength of the sensor node.

Traffic load is represented as:

$$TL_i = \sum_{p=1}^{M} D_p \tag{41}$$

Where, $D_p$denotes transmitted packet size, and Mrepresents the number of processed packets. Lastly, the REGAL-derived embedding Z_i retains the neighbourhood relations, energy stability, and communication dependencies acquired through graph propagation. The overall state representation contains enough context information for the DRL agent to make an intelligent decision regarding the choice of cluster head node.

3.6.3 Action Space

The action space of the proposed DRL architecture represents the set of actions that the learning algorithm can make at any time when making clusters. Each time a communication round is made, the

learner chooses several nodes as cluster heads based on the current state of the network. The action space is defined as:

$$A = \{a_1, a_2, a_3, \dots, a_N\} \tag{42}$$

Where, $a_i = 1$indicates that node $i$is selected as a cluster head, and $a_i = 0$indicates that node $i$operates as a normal member node. The cluster head selection policy is represented as:

$$\pi(a \mid s) = P(A_t = a \mid S_t = s) \tag{43}$$

Where, $\pi(a \mid s)$denotes the probability of selecting action $a$under state s.

The DRL-based framework keeps refining this policy throughout the training period for optimal network performance in the long run. Over numerous interactions with the environment, this framework can learn how to choose nodes that have not exhausted their energy or faced communication saturation. Therefore, this policy will ensure better network conditions.

3.6.4 Reward Function Design

The reward function has an important place in directing the DRL agent to choose energy-efficient cluster heads. The reward function proposed in the framework takes into consideration more than one objective in the network; such as energy balancing, extending the lifetime of the network, load balancing, and minimizing communication cost. The reward function is defined by:

$$R_t = w_1 E_{balance} + w_2 L_{balance} - w_3 C_{comm} \tag{44}$$

Where, $E_{balance}$represents energy balancing reward, $L_{balance}$denotes load balancing reward, C_{comm}indicates communication cost, and $w_1, w_2, w_3$are weighting coefficients. The energy balancing component is computed as:

$$E_{balance} = \frac{1}{N} \sum_{i=1}^{N} \frac{RE_i}{E_0} \tag{45}$$

Where, RE_idenotes residual energy, and E_0represents initial node energy. The load balancing term is expressed as:

$$L_{balance} = 1 - \frac{\sigma_L}{L_{max}} \tag{46}$$

Where, $\sigma_L$denotes load deviation among cluster heads, and L_{max}indicates maximum allowable load. The communication cost component is represented as:

$$C_{comm} = \sum_{i=1}^{N} d(i, C\,H_i)^2 + d(CH_i, BS)^2 \tag{47}$$

Where, $d(i, CH_i)$denotes intra-cluster communication distance, and $d(CH_i, BS)$represents cluster head to sink distance.

To further improve network longevity, an additional lifetime reward term is incorporated:

$$L_t = \frac{N_{alive}}{N} \tag{48}$$

Where, N_{alive}indicates the number of active nodes. The final optimized reward function becomes:

$$R_t = w_1 E_{balance} + w_2 L_{balance} + w_3 L_t - w_4 C_{comm} \tag{50}$$

This multi-objective reward strategy encourages the DRL agent to select cluster heads that preserve energy, distribute network load evenly, and minimize transmission overhead.

3.6.5 Policy Learning Process

The suggested DRL approach utilizes a learning algorithm for selecting policies through repeated interactions with the network environment. At first, the agent engages in exploration, to find the best combinations of clustering and measure their effect on the system's performance. The learning phase is later dominated by the exploitation of those actions that have led to success in the past.

The exploration-exploitation tradeoff is controlled using the ϵ-greedy strategy:

$$a_t = \begin{cases} \text{random action}, & rand < \epsilon \\ \arg\max\ Q(s,a), & otherwise \end{cases} \tag{51}$$

Where, ϵdenotes exploration probability, and $Q(s,a)$represents the action-value function.

The DRL approach makes use of a DNN-based model to estimate the ideal Q-value function. The Q-learning network takes the current network state as input and outputs the anticipated reward value corresponding to each possible cluster head selection action.

The Q-value update mechanism is represented as:

$$Q(s_t,a_t) \leftarrow Q(s_t,a_t) + \alpha[r_t + \gamma \max\ Q(s_{t+1},a) - Q(s_t,a_t)] \tag{52}$$

Where, αdenotes learning rate, $r_t$indicates immediate reward, and γrepresents discount factor. During training, the network parameters are iteratively optimized using gradient descent to minimize prediction error:

$$Loss = (y_t - Q(s_t,a_t))^2 \tag{53}$$

where the target value is defined as:

$$y_t = r_t + \gamma \max\ Q(s_{t+1},a) \tag{54}$$

This iterative learning process helps the DRL algorithm optimize its strategy for selecting cluster heads in varying conditions. With each iteration, the learned strategy becomes more effective at finding stable nodes, ensuring balanced traffic load, and optimizing communication overhead. With the use of REGAL-based embedding together with the adaptive reinforcement learning algorithm, it is possible to achieve an intelligent cluster head selection strategy that will allow improving the lifetime of the network and communication stability.

3.7 Energy-Adaptive Partridge Optimization Algorithm (EA-POA)

The Energy-Adaptive Partridge Optimization Algorithm (EA-POA) is utilized within the proposed Hierarchical Graph Reinforcement Network (HGRN) paradigm to improve upon the decision-making results related to the election of the cluster heads provided by the Deep Reinforcement Learning (DRL) scheme. While the Deep Reinforcement Learning paradigm successfully learns adaptive rules for cluster heads' selection, based on its interaction with the environment, the elected cluster heads' configurations may be subject to the problem of local optimality, poor load balancing, and instability under the condition of dynamic changes. In order to make the clustering process more stable and energy-efficient, an optimization refinement phase based on the utilization of the Population-Based Global Search (PBGS), together with energy considerations, is introduced within the proposed EA-POA approach.

The operational procedure of the developed EA-POA method is shown in Figure 4. Firstly, candidate solutions for the cluster heads are created and their performance is assessed based on the energy-aware fitness function. Secondly, the best solution obtained is then improved via adaptive partridge operations based on energy-aware updates. The process continues to optimize and stabilize the solutions, performing fitness assessment and stability checks repeatedly, until it meets the termination condition, whereby the optimal cluster heads will be sent for further communication purposes.

3.7.1 Motivation for EA-POA

Even though DRL method uses reinforcement learning to find cluster head in an intelligent way using long term reward optimization approach, reinforcement learning by itself cannot ensure that globally optimum clustering structure will be achieved in very dynamic WSNs. In case of continuous learning process, the DRL-based system may achieve local optimum that fulfils the requirement for rewards but does not have long term communication and energy efficiency characteristics. Besides, the reinforcement learning process can be influenced by fast changes in nodes' energy level, resulting in frequent changes of clusters' heads and communication costs.

The limitations of the approach have been addressed in the new framework with the inclusion of the Energy Adaptive Partridge Optimization Algorithm that is used as the second phase of optimization in order to enhance the cluster head selection process provided by DRL. In contrast to the traditional algorithms, EA-POA uses an adaptive population for exploration of optimal solutions.

The proposed EA-POA framework specifically focuses on preserving residual energy, reducing intra-cluster communication distance, balancing communication load, and minimizing unstable cluster head transitions.

By combining DRL-driven decision learning with energy-aware optimization refinement, the proposed framework achieves both adaptive intelligence and global solution stability during cluster head selection.

3.7.2 Population Initialization

In the EA-POA scheme, each optimization agent corresponds to one possible cluster head configuration for the WSNs. The optimization population is generated based on the cluster head candidates generated by the DRL module with other candidate solutions that have been perturbed randomly. The generation of the initialization step guarantees that all candidate solutions satisfy the requirement of coverage and connectivity in the network. For the cluster heads' candidates, the nodes that have enough residual energy and capacity to communicate are chosen. The starting position of the optimization agent is generated as:

$$X_i^{(0)} = LB + rand(0,1) \times (UB - LB) \tag{55}$$

Where, $LB$and UBdenote lower and upper search boundaries, and $rand(0,1)$represents a uniformly distributed random number. This initialization mechanism improves population diversity and prevents premature convergence during optimization.

3.7.3 Energy-Aware Fitness Function

The proposed EA-POA approach adopts a multi-objective fitness function that assesses the effectiveness of various combinations of cluster heads. In this approach, residual energy, intra-cluster distance, load balancing, and cluster stability are evaluated together to make sure that the energy efficiency of communication and reliability is optimized. This can be formulated as:

$$F = \alpha E_{res} + \beta L_{bal} + \gamma S_{stab} - \delta D_{intra} \tag{56}$$

Where, E_{res}denotes residual energy factor, L_{bal}represents load balancing factor, S_{stab}indicates stability factor, D_{intra}corresponds to intra-cluster communication distance, and $\alpha, \beta, \gamma, \delta$are weighting coefficients. The residual energy component is computed as:

$$E_{res} = \frac{1}{K}\sum_{i=1}^{K} \frac{RE_i}{E_0} \tag{57}$$

Where, RE_idenotes residual energy of cluster head i, E_0represents initial node energy, and Kindicates the number of cluster heads. The intra-cluster distance component is calculated using:

$$D_{intra} = \frac{1}{N} \sum_{i=1}^{N} d(i, C\,H_i) \tag{60}$$

Where, $d(i, CH_i)$denotes the distance between node $i$and its assigned cluster head. The load balancing factor is represented as:

$$L_{bal} = 1 - \frac{\sigma_L}{L_{max}} \tag{61}$$

Where, $\sigma_L$denotes load variance among cluster heads, and L_{max}represents maximum communication load. To improve clustering reliability, a stability factor is introduced:

$$S_{stab} = \frac{1}{K} \sum_{i=1}^{K} \frac{T_i}{T_{max}} \tag{62}$$

Where, $T_i$represents cluster head stability duration, and T_{max}denotes maximum allowable operational duration. The proposed fitness function therefore prioritizes cluster head configurations capable of maintaining balanced energy utilization and stable communication while minimizing transmission overhead.

3.7.4 Adaptive Position Update

Upon the identification of promising candidate solutions, the proposed EA-POA methodology employs the revised partridge motion-based strategy for the positioning of optimization agents based on the energy-efficient adaptation scheme. The revised motion process allows candidate solutions to converge towards globally optimized cluster head arrangements.

The adaptive position update equation is represented as:

$$X_i^{t+1} = X_i^t + r_1(P_{best} - X_i^t) + r_2(X_{mean} - X_i^t) \tag{63}$$

Where, X_i^tdenotes the current position of agent i, P_{best}represents the globally best solution, X_{mean}indicates the population mean position, $r_1$and $r_2$are adaptive random coefficients.

Higher residual energy nodes receive more influence in terms of optimization, while energy-depleting nodes get less influence in movement contribution. The resulting adaptive mechanism helps maintain stability during optimization without picking up weaker cluster head candidates. Another factor considered in the energy adaptive process is:

$$\Psi_i = e^{-\mu(1-\frac{RE_i}{E_0})} \tag{64}$$

Where, $\Psi_i$denotes the energy adaptation coefficient, and μcontrols energy sensitivity. The final adaptive update becomes:

$$X_i^{t+1} = X_i^t + \Psi_i[r_1(P_{best} - X_i^t) + r_2(X_{mean} - X_i^t)] \tag{65}$$

This modification allows the optimization process to prioritize energy-stable cluster head configurations while preserving global search capability.

3.7.5 Stability-Based CH Refinement

High cluster head switches lead to high communication overhead and increased routing instability in Wireless Sensor Networks. To solve this problem, the EA-POA scheme employs a stability-oriented approach where stability plays a key role in selecting nodes that can act as stable cluster heads. Stability-oriented refinement considers the consistency of cluster head throughout successive communication phases. In essence, nodes whose energy consumption rate and load are within the stipulated limits are deemed stable and thus have more stability priority during refinement.

The stability score associated with node $i$is computed as:

$$ST_i = \frac{RE_i}{1+SF_i+\sigma_L} \tag{66}$$

Where, ST_idenotes stability score, and $\sigma_L$represents load variation. The refined cluster headset is subsequently selected according to:

$$CH_{opt} = \arg\max(ST_i) \tag{67}$$

The approach also helps in avoiding the creation of clusters when not required and helps in avoiding the breakage in the flow of communication caused by changing the head of clusters from time to time. The approach of using the EA-POA framework described above will be repeated until convergence. The outcome produced by this approach helps in maintaining energy balance and effective communication and stability in the proposed HGRN system.

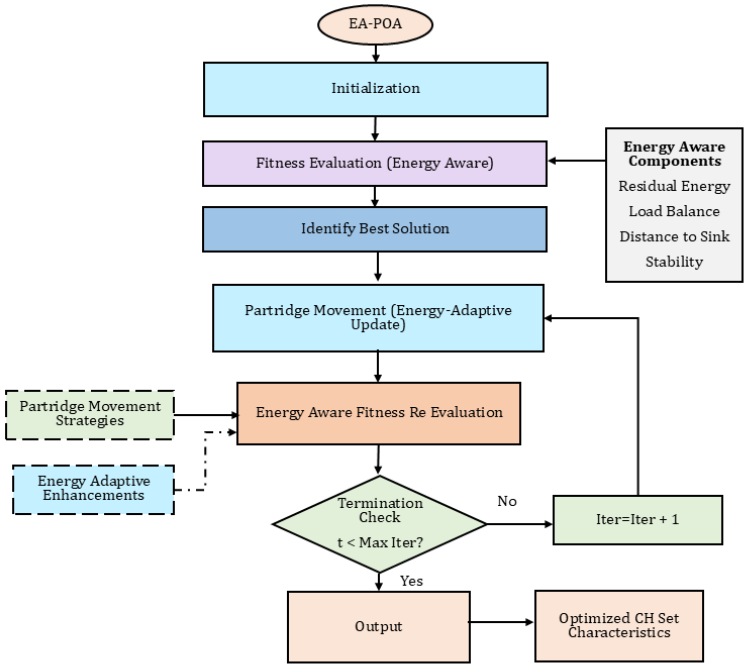


Figure 4. Operational Flow of the Proposed Energy-Adaptive Partridge Optimization Algorithm (EA-POA)

4. Results and Discussions

This subsection provides an overview of the performance evaluation and discussion of the suggested HGRN paradigm in the context of large-scale Wireless Sensor Network settings. In this regard, the efficacy of the suggested method is analysed based on various performance measures, including the energy efficiency measure, network lifetime, packet delivery performance, throughput, delay, cluster stability, load balancing, computational cost, and communication reliability. Additionally, comparisons are made between the suggested technique and conventional clustering schemes to show the ability of the proposed REGAL-based feature learning, DRL-based cluster head selection, and EA-POA-based optimization techniques.

The proposed HGRN model is tested with respect to the simulated Wireless Sensor Network (WSN) with 1000 sensor nodes dispersed in a 100 × 100m sensing area. The initialization value is set to 1J of energy per each sensor node to provide an equal amount of energy supply at the first communication stage. As seen from Table 1, the location of the sink node is set at 50ⓜ, 50 to facilitate the data acquisition and prevent transmission overload. In addition, a transmission range of 30 m and packet size of 4000 bits are chosen to guarantee stability of neighbourhood connection and realistic

sensing communication process, respectively. The whole simulation runs for 10000 communication steps to investigate long-run sustainability and energy consumption behaviour. At the stage of DRL, 500 training periods with a learning rate and discount factor of 0.001 and 0.95, respectively, are adopted to stabilize convergence and make cluster head selection flexible. Additionally, the deep learning algorithm includes three layers with a ReLU function to enhance non-linear decision-making processes.

Table 1. Simulation Parameters of the Proposed HGRN Framework

Parameter	Value
Network Area	100m × 100m
Number of Sensor Nodes	1000
Initial Node Energy	1 J
Sink Position	(50, 50)
Packet Size	4000 bits
Transmission Range	30 m
Simulation Rounds	10000
Data Aggregation Energy	5 nJ/bit
Electronics Energy	50 nJ/bit
Amplifier Energy	100 pJ/bit/m²
DRL Episodes	500
Learning Rate	0.001
Discount Factor (γ)	0.95
Replay Buffer Size	10000
Batch Size	64
Hidden Layers	3
Activation Function	ReLU

From the alive nodes analysis, the developed HGRN model sustains network activity over a much longer period than other models based on clustering. A greater number of alive sensor nodes is retained by the developed algorithm in successive rounds of communication, which shows an even distribution of energy consumption and proper management of clusters during the working of the network. According to Figure 5, the delay in the onset of FND, HND, and LND is another indication of the efficacy of the developed model and its ability to delay the premature death of nodes through REGAL-based energy learning and EA-POA optimization.

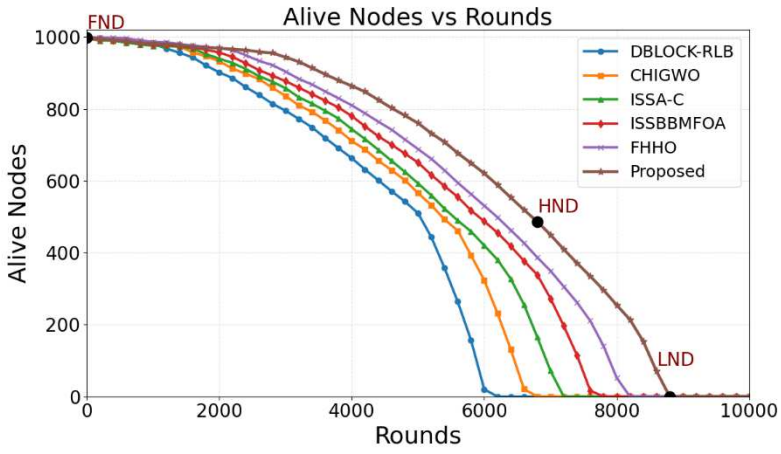


Figure 5. Alive Nodes Versus Communication Rounds Analysis

Through comparative performance analysis, it can be observed that the HGRN framework proposed in this research provides higher efficiency and communication stability than any previously implemented clustering technique. It has been seen that the proposed technique is able to provide network lifetime of 10000 rounds and residual energy of 535 joules, which suggests that energy distribution is efficient and does not lead to early depletion of nodes. From Table 2, the proposed technique provides higher packet delivery ratio of 89.8% as well as reduces the communication delay to 198 ms, which ensures reliable and fast transfer of data through WSNs. Further, the number of packets transmitted increases to 6350. Energy consumption decreases to 1915 joules whereas the computational cost remains at 54%.

Table 2. Comparative Performance Evaluation of the Proposed HGRN Framework

Method	Network Lifetime (Rounds)	Residual Energy (J)	PDR Ratio (%)	Delay (ms)	Throughput (Packets)	Energy (J)	Computation Cost (%)
DBLOCK-RLB	7200	118	70.5	298	4850	2520	78
CHIGWO	7800	176	75.8	248	5100	2410	73
ISSA-C	8400	248	80.2	236	5380	2285	69
ISSBBMFOA	9000	332	82.8	225	5650	2160	64
FHHO	9600	418	86.3	214	5920	2050	59
Proposed	10000	535	89.8	198	6350	1915	54

The dead node evaluation shows that the developed HGRN framework greatly prolongs the time at which the node failures begin propagating in the whole network lifetime in comparison to other clustering algorithms. The developed method shows gradual growth of dead nodes through each round of communication, implying good energy consumption and even distribution of tasks among the sensor nodes. As shown in Figure 6, the developed HGRN framework is capable of delaying the time up to when all the nodes become exhausted by virtue of using the REGAL method for the energy-aware embedding generation and EA-POA algorithm for optimizing clusters.

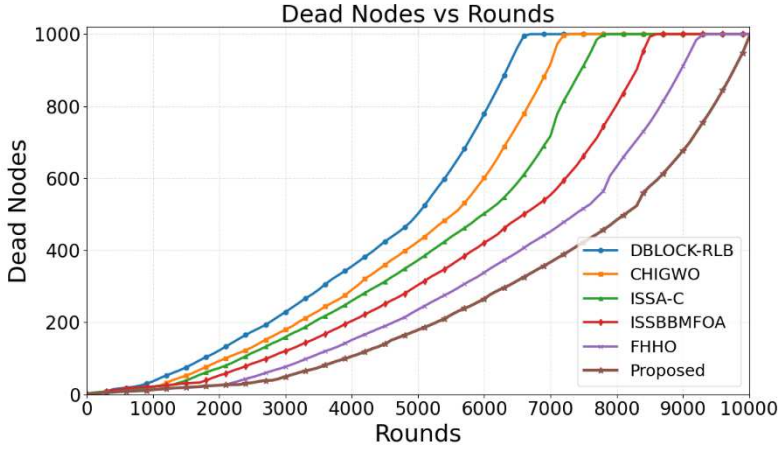


Figure 6. Dead Nodes Versus Communication Rounds Analysis

The findings in improvement analysis reveal the high effectiveness of the HGRN in improving the performance of WSNs in terms of large-scale deployment. The HGRN framework provides an average improvement in the network lifetime of 38.9%, indicating its effectiveness in striking the right balance between energy consumption and avoiding the depletion of node resources too early. From Table 3, one can see that there is an increase in the packet delivery ratio of 27.4%, which means that the proposed method is effective in ensuring reliable packet transmission between sensor nodes. The

reduction in communication delay of 33.6% indicates that there is effective selection of cluster heads and routing behavior, respectively. Also, the decrease in energy consumption by 24.0% implies that the HGRN framework enhances the efficiency in the consumption of energy by WSNs. There is also an improvement in the throughput of 30.9%.

Table 3. Performance Improvement Analysis of the Proposed HGRN Framework

Metric	Improvement (%)
Network Lifetime Improvement	38.9%
Packet Delivery Ratio Improvement	27.4%
Delay Reduction	33.6%
Energy Consumption Reduction	24.0%
Throughput Improvement	30.9%

From the residual energy perspective, the introduced HGRN framework is more stable and balanced in terms of energy consumption than any other method employed previously in similar frameworks. This is because the presented framework demonstrates high levels of residual energy through an increased number of communication rounds thanks to efficient cluster heads' adaptation and energy-awareness routing strategy. As shown in Figure 7, the proposed system postpones battery drain for a longer period due to using the REGAL-based learning features and EA-POA technique, thus prolonging the operational life cycle of nodes. The progressive decrease in energy also suggests that communication overhead and load balancing were successfully accomplished.

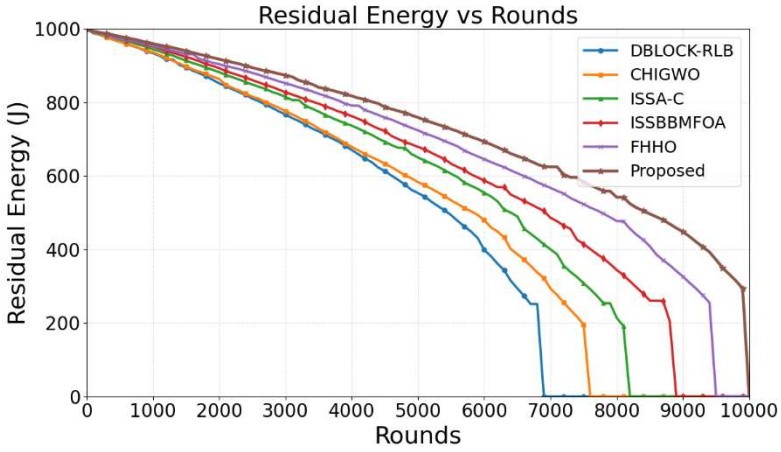


Figure 7. Residual Energy Versus Communication Rounds Analysis

From the comparative analysis of the energy distribution performance of the systems under study, it can be noted that the proposed HGRN framework ensures better load balancing and stable energy utilization among sensor nodes. The proposed algorithm produces the least value of energy variance of 0.124, meaning that the energy consumption is evenly distributed without exerting much pressure on certain cluster heads. In addition, as indicated in Table 4, the proposed framework also obtains a load balancing factor of 0.95. This result indicates that the proposed feature learning and optimization approaches based on the REGAL and EA-POA are effective in ensuring balanced communication load between clusters. The improvement in terms of load balancing behaviour and energy fluctuations greatly eliminates premature failure of nodes.

Table 4. Comparative Analysis of Energy Variance and Load Balancing Performance

Method	Energy Variance	Load Balancing Index
DBLOCK-RLB	0.248	0.74
CHIGWO	0.221	0.78
ISSA-C	0.198	0.82

ISSBBMFOA	0.172	0.87
FHHO	0.149	0.91
Proposed	0.124	0.95

From the throughput analysis results, the suggested HGRN architecture provides high data transmission capacity even after several communication periods when compared to other clustering schemes. The suggested approach gives high throughput results due to optimal cluster formation, consistent routing activities, and packet transmission processes. As seen from Figure 8, the throughput deterioration rate of the suggested framework is relatively low even after the late stage of communication because of low energy loss and packet delivery interruptions. With the help of REGAL-based energy-aware embedding learning and EA-POA-based clustering optimization techniques, the proposed HGRN architecture supports uninterrupted data transmission without any delay or congestion problems.

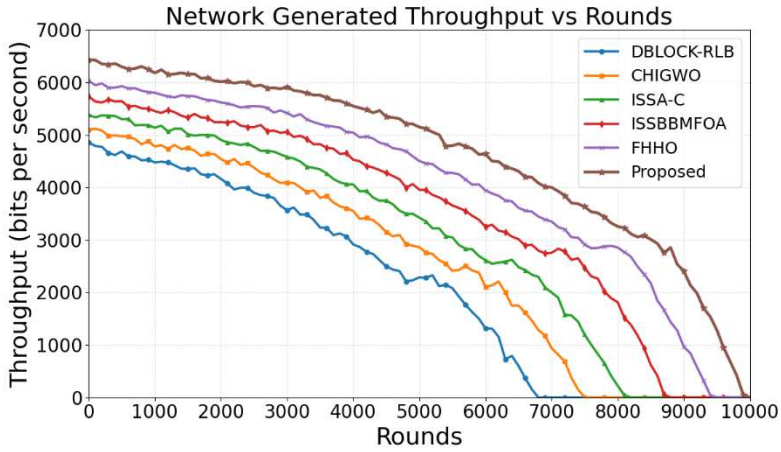


Figure 8. Network Generated Throughput Versus Communication Rounds Analysis

The computational results show that the designed HGRN approach can effectively scale while offering an optimized intelligent cluster head selection mechanism for large-scale WSNs. Specifically, the designed HGRN scheme offers a computational time complexity of O(n log n), which implies that the fusion of REGAL-based graph learning model, DRL-based decision making, and EA-POA-based optimization does not cause any high computational costs during the clustering process. In terms of computational space complexity, as shown in Table 5, the HGRN framework keeps a decent space complexity of O(n + k), where k stands for additional space related to embedding learning and optimization parameters. Regarding higher computational complexity exhibited by traditional methods, the designed HGRN scheme is more appropriate for large-scale WSNs.

Table 5. Computational Complexity Analysis of the Proposed HGRN Framework

Method	**Time Complexity**	**Space Complexity**
DBLOCK-RLB	$O(n^2)$	O(n)
CHIGWO	$O(n^2)$	O(n)
ISSA-C	O(n log n)	O(n)
ISSBBMFOA	O(n log n)	O(n)
FHHO	O(n log n)	O(n+k)
Proposed HGRN	O(n log n)	O(n+k)

Analysis of the packet delivery ratio indicates that the developed framework ensures effective communication behaviour even as the number of sensors grows in the wireless network. The proposed

framework manages to yield better PDR figures even at larger numbers of sensor nodes, reflecting that routing and management activities performed in the system work effectively and yield optimal results. As shown in Figure 9 below, the decrease in the figure of PDR in the proposed framework is notably smaller than that in case of existing clustering techniques; thus, it is evident that the developed framework works effectively in terms of energy-aware feature learning and adaptive cluster management via deep reinforcement learning.

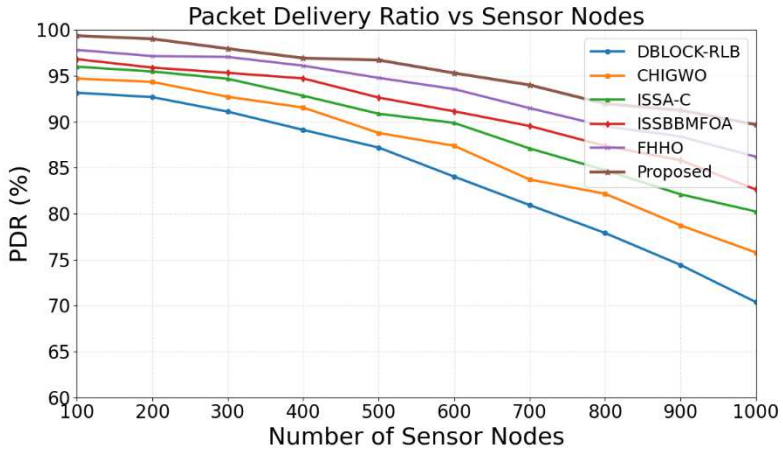


Figure 9. Packet Delivery Ratio Versus Number of Sensor Nodes Analysis

According to the analysis of the cluster head evaluation results, the HGRN framework has shown high levels of stability and reliability for the clustering operation under dynamically changing WSN environment. This method has gained the cluster head stability index score of 0.93, showing that chosen cluster heads are active for more extended periods without any disruptions of the network topology. Moreover, based on Table 6, it has been proven that the proposed framework has managed to attain the cluster head selection accuracy level of 95.7%. This shows that REGAL embedding learning and DRL approach were quite effective in selecting cluster heads. Also, the frequency of cluster reconstruction was reduced to only 18. Therefore, we can conclude that the proposed HGRN framework has significantly enhanced the stability, reliability of communication, and sustainability of the network.

Table 6. Comparative Analysis of Cluster Head Stability and Selection Performance

Method	**CH Stability Index**	**CH Selection Accuracy (%)**	**Re-clustering Frequency**
DBLOCK-RLB	0.61	71.2	42
CHIGWO	0.67	76.8	37
ISSA-C	0.73	81.4	32
ISSBBMFOA	0.80	86.1	28
FHHO	0.86	90.2	24
Proposed HGRN	0.93	95.7	18

The results obtained from the visual analysis clearly show that the proposed HGRN framework sustains a stable state of operation despite the presence of complicated sensing environments and fluctuating conditions for communication within the Wireless Sensor Networks. It is evident from the representation of the network shown above that the proposed method of clustering enables the maintenance of connectivity alongside ensuring effective transfer of data within the nodes. As seen from Figure 10, the proposed HGRN can effectively minimize any disruption in the process of communication via proper coordination among the cluster heads as well as efficient use of energy within the sensing field.

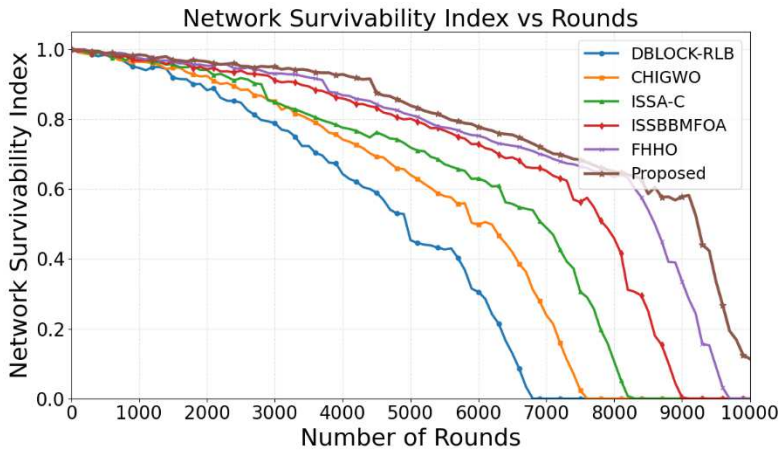


Figure 10. Visual Representation of Stable Communication Behaviour in the Proposed HGRN Framework

Based on the results of the packet transmission analysis, the suggested HGRN model provides high communication reliability by reducing packet loss within the process of network transmission. In particular, the proposed algorithm achieves the smallest packet loss ratio of 10.2%, showing that the REGAL-based clustering and adaptive routing model guarantees communication link stability between sensor nodes. According to Table 7, the ratio of successfully transmitted packets amounts to 89.8%, proving that the suggested approach ensures efficient forwarding of data collected from sensors with minimum packet transmission failures and low routing instability. The enhanced packet transmission behaviour is provided owing to energy-efficient cluster head selection, traffic load balancing, and efficient communication management.

Table 7. Comparative Analysis of Packet Transmission Performance

Method	**Packet Loss Ratio (%)**	**Successful Packet Transmission (%)**
DBLOCK-RLB	29.5	70.5
CHIGWO	24.2	75.8
ISSA-C	19.8	80.2
ISSBBMFOA	17.2	82.8
FHHO	13.7	86.3
Proposed HGRN	10.2	89.8

The energy consumption analysis shows that the proposed architecture of the HGRN can still achieve low energy consumption despite the growing number of sensor nodes in the wireless sensor network. It is worth noting that the proposed methodology consistently ensures reduced energy consumption in comparison with other clustering techniques, which means efficient handling of the communication process and proper functioning of cluster heads. As depicted in Figure 11, the increasing speed of energy consumption for the proposed system is significantly minimized due to the application of energy-aware embedding generation based on REGAL and EA-POA-based cluster head selection and management.

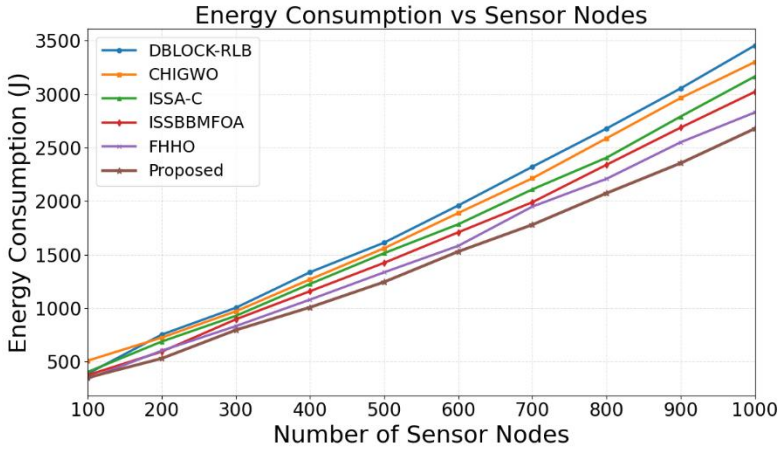


Figure 11. Energy Consumption Versus Number of Sensor Nodes Analysis

As can be seen from survivability, survivability analysis shows that the designed HGRN model possesses better long-term survivability compared to other clustering methods used in WSNs. It gives the best survivability ratio, which equals 0.89 and means that more sensor nodes survive during the whole process of communication. According to Table 8, better survivability is ensured due to balanced energy consumption, effective cluster head selection and reliable routing in WSN. Using REGAL and energy awareness learning in EA-POA helps overcome early exhaustion of sensor nodes and ensure network sustainability.

Table 8. Comparative Analysis of Network Survivability Performance

Method	Survivability Index
DBLOCK-RLB	0.51
CHIGWO	0.58
ISSA-C	0.65
ISSBBMFOA	0.72
FHHO	0.80
Proposed HGRN	0.89

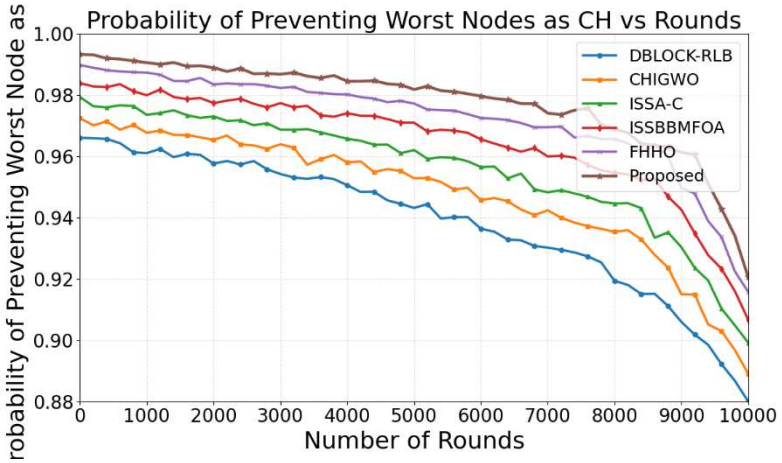


Figure 12(a). Probability of Preventing Worst Nodes as Cluster Head Versus Rounds Analysis

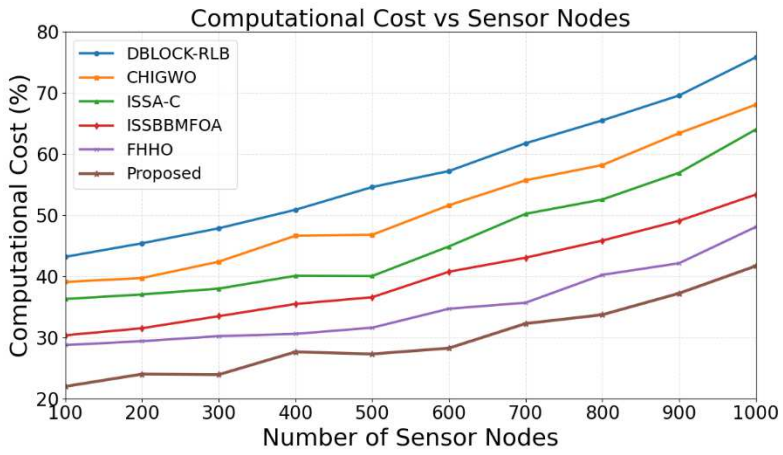


Figure 12(b). Computational Cost Versus Number of Sensor Nodes Analysis

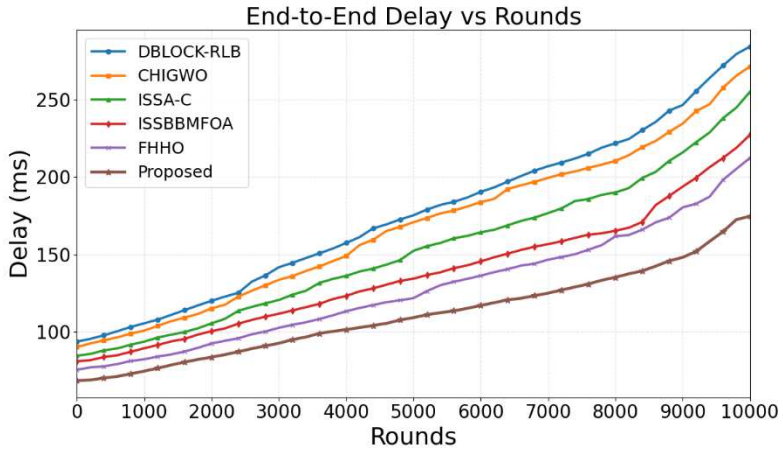


Figure 12(c). End-to-End Delay Versus Communication Rounds Analysis

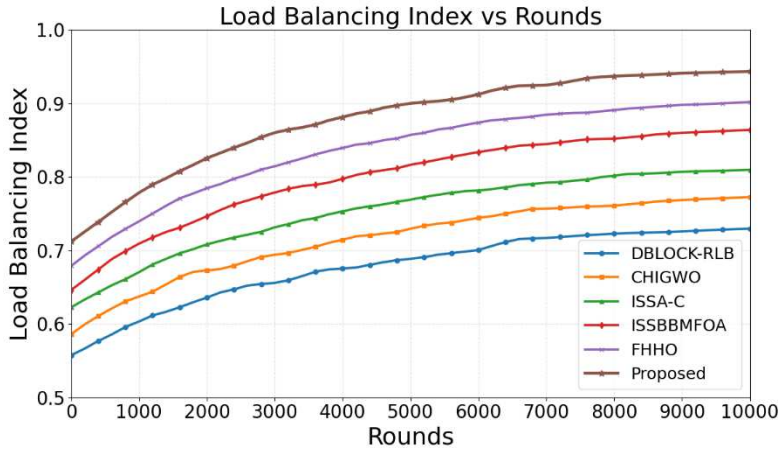


Figure 12(d). Load Balancing Index Versus Communication Rounds Analysis

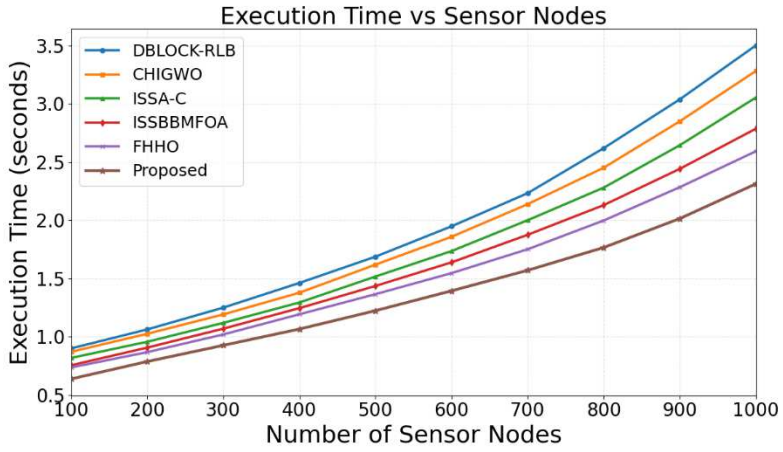


Figure 12(e). Execution Time Versus Number of Sensor Nodes Analysis

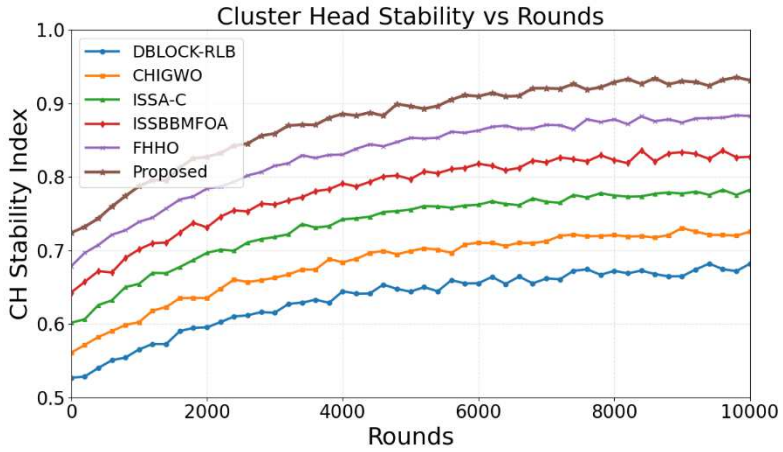


Figure 12(f). Cluster Head Stability Versus Communication Rounds Analysis

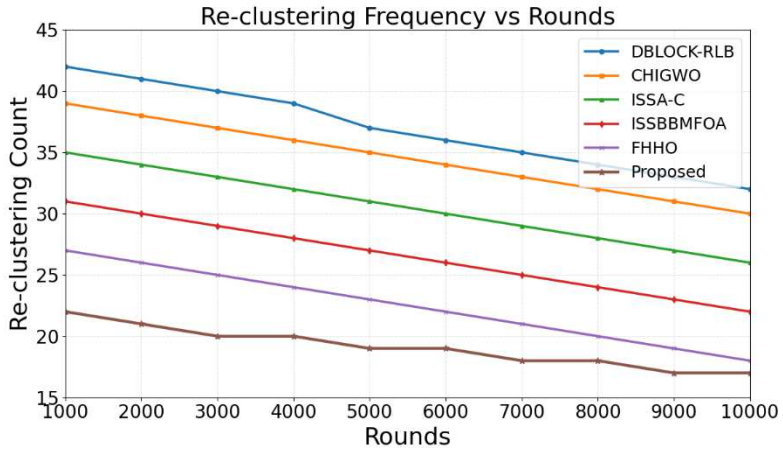


Figure 12(g). Re-clustering Frequency Versus Communication Rounds Analysis

As seen from the thorough performance evaluation of the HGRN framework, it outperforms other clustering algorithms on several measures used to assess network performance in large WSNs. The probability of avoiding unstable nodes to be selected as cluster heads is much higher when the proposed framework is used, meaning better cluster stability as well as energy-awareness while deciding on cluster heads. This can be seen in Figure 12(a) by how REGAL-based temporal energy learning with adaptive DRL optimization allows for not selecting weak nodes as cluster heads.

Moreover, as is seen in Figure 12(b), the computational overhead of the proposed approach is still less than that of traditional ones despite an increase in the number of sensors.

Further, the load balancing results obtained in Figure 12(d) show that the proposed framework can sustain high balancing index values during increasing number of communication rounds, which helps in maintaining minimal traffic concentration and communication congestion among the cluster heads. Additionally, the time taken by the proposed system to execute tasks, represented in Figure 12(e), proves that the proposed framework can sustain scalable operations with bounded processing costs, even at high network deployment densities. Furthermore, the study of stability of cluster heads conducted in Figure 12(f) shows that the proposed technique sustains high stability of operations among the cluster heads for longer periods of time. This further avoids any unnecessary change in topology and any disturbances during communication sessions.

5. Conclusion

The developed approach is based on the proposed Hierarchical Graph Reinforcement Network (HGRN) architecture for the efficient and intelligent clustering head selection in Wireless Sensor Networks. The framework includes GNN topology learning, REGAL-driven energy-aware embedding generation, DRL-based adaptive clustering head selection, and EA-POA-based optimization for balanced communication control. Specifically, the proposed HGRN represents sensor nodes as graphs and makes the use of temporal residual energy analysis to identify stable nodes at each stage of cluster creation. The experiments have shown that the developed framework leads to an increased network lifetime, residual energy, throughput, packet delivery rate, and communication stability. The results showed that HGRN achieves 10000 rounds network lifetime, 535J residual energy, 6350 packets throughput, and 89.8% packet delivery ratio while decreasing delay and energy consumption. Besides, effective load balancing, cluster stability, survivability, and lower packet losses proved the applicability of the HGRN framework for sustainable communication in WSNs. Further investigations can be directed to mobile sink node optimization, federated reinforcement learning, blockchain-based secure routing protocols, edge computing, and energy harvesting in IoT-powered environments.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Conflict of interest

The authors declare no conflict of interest.

Data Availability

Data available on request from the authors.

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References

[1] Benelhouri, Abdelkader, Hafida Idrissi-Saba, and Jilali Antari. "An evolutionary routing protocol for load balancing and QoS enhancement in IoT enabled heterogeneous WSNs." *Simulation Modelling Practice and Theory* 124 (2023): 102729.

[2] Chen, Ruizhi. "Optimizing wireless sensor network topology with node load consideration." *Virtual Reality & Intelligent Hardware* 7, no. 1 (2025): 47-61.

[3] Ridwan, Mohammad, Teguh Wahyono, Irwan Sembiring, and Rini Darmastuti. "Enhancing Wireless Sensor Network performance: A Novel Adaptive Grid-Based Clustering Hierarchy protocol." *Array* 27 (2025): 100440.

[4] Shalu, Berin, and Vergin Raja Sarobin. "Minimal Sensor Node Selection (MSNS), an Evolutionary Algorithm for Target Coverage in Clustered Wireless Sensor Networks." *Results in Engineering* (2026): 110295.
[5] Pravin, R. Anto, K. Murugan, C. Thiripurasundari, Prasanna Ranjith Christodoss, R. Puviarasi, and Syed Ismail Abdul Lathif. "Stochastic cluster head selection model for energy balancing in IoT enabled heterogeneous WSN." *Measurement: Sensors* 35 (2024): 101282.
[6] Juwaied, Abdulla, and Lidia Jackowska-Strumillo. "DL-HEED: A deep learning approach to energy-efficient clustering in heterogeneous wireless sensor networks." *Applied Sciences* 15, no. 16 (2025): 8996.
[7] Vaggu, Nagesh Mallaiah, and Ravi Sankar Barpanda. "DBlock-RLB: An energy efficient framework for intelligent routing and trading based load balancing in SDWSN environment." *Ad Hoc Networks* 159 (2024): 103475.
[8] Aleem, Abdul, and Rajesh Thumma. "Optimized energy-efficient knapsack algorithm for intelligent cluster head selection in wireless sensor networks." *Engineering, Technology & Applied Science Research* 15, no. 2 (2025): 22089-22094.
[9] Sefati, Seyed Salar, Bahman Arasteh, Razvan Craciunescu, and Ciprian-Romeo Comsa. "Intelligent congestion control in wireless sensor networks (WSN) based on generative adversarial networks (GANs) and optimization algorithms." *Mathematics* 13, no. 4 (2025): 597.
[10] Prasanth, V. S., A. Mary Posonia, and A. Parveen Akhther. "Effective ensemble-based intrusion detection and energy efficient load balancing using sunflower optimization in distributed wireless sensor network." *Multimedia Systems* 30, no. 4 (2024): 223.
[11] Sharma, Aarti, and Ankush Kansal. "Enhanced CH selection and energy efficient routing algorithm for WSN." *Microsystem Technologies* 31, no. 3 (2025): 735-747.
[12] Krishna Sowjanya, K., and S. K. Mouleeswaran. "Enhancing cloud security with intelligent load balancing and malicious request classification." *Cluster Computing* 28, no. 1 (2025): 41.
[13] Rajkumar, G. Vinoth, and N. Muthukumaran. "Efficient load balancing and energy conservation protocol for WSN based on DBDQN and wild geeze migration optimization algorithm." *Telecommunication Systems* 89, no. 1 (2026): 29.
[14] Biswal, Sanjay Kumar, Tusharkanta Samal, Prabhudutta Mohanty, and Ram Chandra Barik. "Design of a novel load balanced multi-sink based hierarchical data gathering protocol for wireless sensor networks." *Wireless Networks* 31, no. 2 (2025): 1497-1514.
[15] Sennan, Sankar, Somula Ramasubbareddy, Rajesh Kumar Dhanaraj, Anand Nayyar, and Balamurugan Balusamy. "Energy-efficient cluster head selection in wireless sensor networks-based internet of things (IoT) using fuzzy-based Harris hawks optimization." *Telecommunication Systems* 87, no. 1 (2024): 119-135.
[16] Shah, Idris Afzal, and Mushtaq Ahmed. "FK-means RA: Fuzzy K-means clustering routing algorithm for load balancing in wireless sensor networks." *Wireless Personal Communications* 130, no. 2 (2023): 1071-1083.
[17] Kaur, Kirandeep, and Satinder Kaur. "Bio-inspired hybrid algorithm for load balancing and lifetime extension in sensor networks." *Sādhanā* 51, no. 2 (2026): 90.
[18] Sefati, Seyed Salar, Mehrdad Abdi, and Ali Ghaffari. "QoS-based routing protocol and load balancing in wireless sensor networks using the markov model and the artificial bee colony algorithm." *Peer-to-Peer Networking and Applications* 16, no. 3 (2023): 1499-1512.
[19] Srivastava, Ankita, and Pramod Kumar Mishra. "IDA: Improved dragonfly algorithm for load balanced cluster heads selection in wireless sensor networks." *Peer-to-Peer Networking and Applications* 17, no. 4 (2024): 2315-2333.
[20] Alsuwat, Hatim, and Emad Alsuwat. "Energy-aware and efficient cluster head selection and routing in wireless sensor networks using improved artificial bee Colony algorithm." *Peer-to-Peer Networking and Applications* 18, no. 2 (2025): 65.
[21] Dawood, M. Sheik, S. Sridevi, C. Sujatha, and Janjhyam Venkata Naga Ramesh. "Enhanced cluster head selection and energy efficient routing using optimized dual-path multi-scale attention

guided network in WSN environment." *Peer-to-Peer Networking and Applications* 19, no. 1 (2026): 22.
[22] Lekhraj, Alok Kumar, and Anoj Kumar. "Load balanced and optimal clustering in WSNs using grey wolf optimizer." *International Journal of System Assurance Engineering and Management* 15, no. 7 (2024): 2950-2964.
[23] Singh, Yash Veer, Shadab Khan, Prasant Singh Yadav, Vinay Kumar Singh, and Prashant Tomer. "Adaptive Cluster Head Selection in IoT-Based WSNs Using Enhanced Binary Hiking Optimization." *National Academy Science Letters* (2026): 1-10.
[24] Singh, Yash Veer, Harikesh Singh, Vinay Kumar Singh, Pushpendra Singh, and Ashok Kumar Yadav. "ISAO: An Improved Snow Ablation Optimizer for Energy-Efficient Cluster Head Selection in Wireless Sensor Networks." *National Academy Science Letters* (2026): 1-10.
[25] Ambareesh, S., Pundalik Chavan, S. Supreeth, Rajesh Nandalike, P. Dayananda, and S. Rohith. "A secure and energy-efficient routing using coupled ensemble selection approach and optimal type-2 fuzzy logic in WSN." *Scientific reports* 15, no. 1 (2025): 38.
[26] Alshammri, Ghalib H. "Enhancing wireless sensor network lifespan and efficiency through improved cluster head selection using improved squirrel search algorithm." *Artificial Intelligence Review* 58, no. 3 (2025): 79.
[27] Rajalakshmi, M., and S. Ponni Alias Sathya. "Smart pareto-optimized genetic algorithm for energy-efficient clustering and routing in wireless sensor networks." *Scientific Reports* 15, no. 1 (2025): 35065.
[28] Janakiraman, Sengathir, and M. Deva Priya. "Improved salp swarm and bare bones mayfly optimization algorithm-based CH selection and sink node mobility for improving network longevity in WSNs." *Sādhanā* 50, no. 2 (2025): 113.
[29] Qu, Yanhui, Yingyi Qu, Zhiqiang Zhu, Liang Deng, and Xiao Xu. "Intelligent unequal clustering in wireless sensor networks using a game theoretic and evolutionary strategy." *Scientific Reports* 15, no. 1 (2025): 32992.
[30] Rao, Chuchu, Mingqi Kan, Peng Zhou, and Yeshen Lan. "A novel multi objective energy efficient clustering optimization scheme based on heuristic intelligence for wireless sensor networks." *Scientific Reports* 15, no. 1 (2025): 36988.
[31] Energy-Efficient Cluster Head Selection in Wireless Sensor Networks Using an Improved Grey Wolf Optimization Algorithm
[32] Banoth, Sanjai Prasada Rao, Biswa Mohan Sahoo, Anil Kumr Gankotiya, Abhishek Kumar Pandey, and Arvind Dhaka. "An intelligent algorithm based optimized clustering method for energy harvesting WSN." *Scientific Reports* (2025).
[33] Yogaraja, G. S. R., M. N. Thippeswamy, and K. Venkatesh. "Dynamic Task Scheduling and Load Balancing in Cloud WSN-IoT Using Swho." *SN Computer Science* 7, no. 3 (2026): 278.
[34] Ramani, G., and Amarendra K. "An optimized energy management and load balancing system based on cluster head selection for the vehicular network communication." *Multimedia Tools and Applications* 83, no. 31 (2024): 75461-75482.
[35] Kundu, Mainak, Ria Kanjilal, and Ismail Uysal. "Intelligent clustering and adaptive energy management in wireless sensor networks with KDE-based deployment." Sensors 25, no. 8 (2025): 2588.