10.48047/jocaaa.2024.32.01.66

An Energy-Efficient and State-Aware Path Selection Technique in the Internet of Things

A. Thomas Felix[1] and P. Calduwel Newton[2]
[1]Department of Computer Science, Government Arts College, Kulithalai, India, Affiliated to Bharathidasan University, Tiruchirappalli
E-mail: athomasfelix@gmail.com
[2]Department of Computer Science, Government Arts College, Trichy-22, India, Affiliated to Bharathidasan University, Tiruchirappalli
E-mail: calduwel@gmail.com

Abstract

Recent developments in sensor and networking technologies have driven the growth of Internet of Things (IoT) applications. In non-rechargeable environments, IoT devices are decentralized systems with autonomous nodes that are limited in resources due to a lack of continuous connectivity or battery life. Energy consumption is crucial when designing communication solutions for the IoT, as poor connections tend to have longer delivery times and are less reliable; retransmissions also increase energy consumption. Optimizing the quality of connections can dramatically impact end-to-end delivery times and network longevity. However, the Quality of Service (QoS) requirements for selecting the right IoT services are complex, and managing energy consumption in sensors is essential. It involves evaluating key performance indicators such as Residual Energy (RE) and Packet Delivery Ratio (PDR), which are used to make decisions about the responsibility for packet transmissions. To this end, hybridizing Genetic Algorithms (GA) with Grey Wolf Optimization (GWO) aims to achieve better localization of nodes, reduce Energy Consumption (EC) in Sensor Nodes (SN), and find the optimal path to the Base Station (BS), ultimately helping to conserve the energy of SNs and prolong the life of IoT networks. The Low-Energy Adaptive Clustering Hierarchy (LEACH) is designed to cluster sensor nodes and extend the network's lifespan. The objective of this paper is to develop a modified version of LEACH by incorporating adaptive clustering, resulting in multi-hop LEACH. Simulations demonstrate that the proposed technique minimizes EC and enhances network longevity, resulting in an increase in average RE of up to 5.26% and a decrease in average EC of up to 12.4%, while boosting PDR to 98.25%. Utilizing GAs strengthens the network's robustness.

Keywords

Sensor nodes, genetic algorithm, grey wolf optimization, localization, anchor nodes, chromosomes.

1. Introduction

The IoT is reshaping areas such as environmental monitoring, healthcare, smart cities, and industrial automation, but it faces challenges related to energy use. Efficient energy management is crucial for extending network life, reducing maintenance, and ensuring sustainability. The routing process, which directs the flow of information, is also critical.

10.48047/jocaaa.2024.32.01.66

Inefficient protocol choices can deplete energy, cause network fragmentation, and degrade performance. Energy-aware routing schemes aim to enhance the proficiency of the IoT ecosystem. Traditional routing protocols often fall short in dynamic, energy-limited environments, relying on unsuitable parameters or fixed paths that can lead to premature node failure due to uneven energy distribution. In complex scenarios, bio-inspired algorithms such as GWO and GAs demonstrate significant potential. GAs utilizes concepts from Darwinian evolution for solutions, while GWO draws on the social behavior of grey wolves, excelling in exploration and exploitation. A hybrid approach that combines both GA and GWO, known as GA-GWO, leverages the comprehensive search capabilities of GA with the efficient local search of GWO. This approach addresses issues of premature convergence in GA and local optima in GWO. The GA-GWO protocol selects energy-efficient paths, considering factors that impact network lifespan and data transmission success. It emphasizes the evaluation of routing performance metrics, such as RE and PDR, with a focus on distributing residual energy evenly to prevent hotspot formations that drain energy. Balanced energy use prolongs the network's life. PDR, which indicates data transmission efficiency and reliability, is vital in the IoT to ensure data integrity while managing energy. The challenge lies in balancing these aspects to achieve high PDR for stable routes, ensuring reliable sensor data delivery. This paper introduces a new GA-GWO routing technique for energy-efficient and reliable IoT solutions, focusing on residual energy and PDR to sustain networks.

2. Related Works

QoS-aware selection in mobile IoT devices is analyzed, emphasizing the issues entailed in mobility and the scarce power available to IoT devices as the root causes of changes in service quality. In addition to durability, research suggests that a strategic choice of services can contribute to stability in a more interconnected world. Among these techniques, one that targets extending the network lifetime in fully connected Wireless Sensor Networks (WSNs) is the Advanced Exhaustive Search Algorithm (AESA) combined with a Single-Objective Genetic Algorithm (SOGA), primarily focused on aspects such as closeness, meeting, link efficiency, and network lifetime [1]. [2] advances in applying a combined GA and Particle Swarm Optimization (PSO) with a K-Nearest Neighbors (KNN) algorithm to address complex IoT systems' resource management problems, a potential key issue for applications such as smart grids or connected vehicles. [3, 4] also examine advances in localization, routing, and security, emphasizing the importance of anchor node density in ensuring accurate data transmission in networks under high contention. Additionally, the energy efficiency of the tree-based routing algorithm is evaluated by minimizing energy costs through the selection of branch configurations that lead to lower energy consumption, providing multi-layer reasoning, and positioning the base station at the heart [5].

Addressing the efficiency of energy and information in WSNs based on IoT for smart agriculture raises various questions, as it considers problems related to the inefficient use of bandwidth and the emergence of high energy requirements that decrease the network's potential lifetime and reliability. An aggregate formal technique is suggested for developing the IoT [6]. One may be found in the more general cluster size of Cluster Heads (CHs) and secure routing

10.48047/jocaaa.2024.32.01.66

protocols for dynamic networks, where a fitness function based on distance is evaluated depending on various factors, including the distance to the BS and the node's energy [7]. Finally, the increasing need to optimize coverage and routing for improved performance of IoT devices would make swarm intelligence, such as Ant Colony Optimization (ACO) and PSO, much more popular [8]. In [9], the authors describe the Enhanced Swarm Distributed Energy-Efficient Clustering Scheme (ES-DEEC), which utilizes a Hybrid PSO-Grey Wolf Optimizer for optimal resource allocation and clustering. The routing is improved by using a swarm optimization technique [10].

The authors in [11] indicate that energy scarcity in the sensor nodes is one of the challenges to overcome, affecting the network lifetime and dependability. These conventional routing models tend to result in an uneven distribution of the load and energy depletion. The work in [12] focuses on the energy management of IoT networks. It addresses network lifetime and throughput issues by optimizing CH selection based on RE and distance from the BS. The work in [13] presents a separate and scalable multipath routing protocol that combines multipath routing and clustering, selecting CHs based on reliability scores using Dempster-Shafer's evidential theory. Additionally, [14] examines radio-frequency energy harvesting as a solution to energy limitations when choosing a CH. In [15], an Elite-Opposition-based Learning strategy (EOL) is coupled with the Tuna Optimization Algorithm (TOA) to enhance clustering processes by considering them based on residual energy and node degree, thereby optimizing both energy and distance.

[16] presents an extension to the IPv6 Routing Protocol for Low-power and Lossy Networks (RPL) for routing by providing an adaptive clustering using a genetic algorithm and advanced prediction capabilities using a neural network. A central Software-Defined Networking (SDN) controller, which administers control over routing, topology discovery, cluster formation, and prediction, is responsible for this mechanism. An alternative to these issues of geographic routing is the proposed energy-efficient geographic (EEG) routing, presented in [17], which employs fuzzy logic for path optimization and a Harris Hawk Optimization (HHO) algorithm. Further, a clustering approach to simulate packet forwarding in Gaussian-distributed and uniform node distribution for efficient localization of sensor nodes in a resource-constrained environment, using PSO-GWO and Whale Optimization Algorithm (WOA), is presented in [18-20].

Regarding black hole attacks in IoT devices, the authors address the problem with the Secure Routing with Whale Optimization Algorithm (SRWOA) to enhance security and energy efficiency within the network [21]. Focusing on the energy consumption problem in IoT networks, particularly in massive sensor deployments, the authors propose the EECR-IoT protocol, which builds upon the divide-and-conquer quadtree and a dynamic multi-hop LEACH for clustering. The neural network multi-hop LEACH (NN_MH_LEACH) is based on an adapted K-means algorithm for selecting cluster heads, which considers Euclidean distance, residual energy metrics, and multi-hop communication in the network to reduce EC further [22, 23]. Concerns about long convergence time, excessive energy consumption, and delay even in larger-scale networks are also addressed, underlining the emphasis on energy-efficient data transmission in IoT. Additionally, since battery-powered devices require substantial energy to

10.48047/jocaaa.2024.32.01.66

capture and transmit data, these issues are exacerbated, highlighting a problem with current protocols regarding overhead and scalability. This method addresses the imbalanced distribution of energy among CHs, which can lead to the WSN failing due to limited node lifespan and the ineffectiveness of traditional routing in prolonging node life, thereby extending the network's lifespan [24-27].

Specifically, the focus is on enhancing power efficiency in mesh networks based on the Thread protocol, which applies to low-power IoT and WSN use cases. The authors suggest using a GA for mono-objective optimization to address this issue. The primary goal is to enhance the energy efficiency of WSNs by utilizing GAs to improve routing and the data delivery ratio, while minimizing the energy spent transmitting this data [28-29]. [30] focuses on energy efficiency and QoS between the LEACH and K-means algorithms in mobile IoT, as well as the balance between energy consumption and QoS. It also features dynamic CH selection, which helps prevent fast node depletion and reduce EC, especially in cases of node mobility.

2.1 Research Gaps

The distinct algorithms reveal key processes, network conditions, and inherent problems in achieving global energy optimization. However, essential limitations in the research remain, leaving outstanding questions related to critical performance metrics.

1. Limited radio range and computing capabilities represent a significant issue for IoT networks, and they are significantly associated with the use of non-rechargeable batteries in sensor nodes.
2. Energy-saving routing protocols are crucial for enhancing the operational lifespan of IoT networks, provided they do not create unfair "hot spots" and "energy holes."
3. Because the failure of a single node can dramatically impact the performance of the whole network, reliability and energy efficiency are sometimes assessed by the time to first node failure.
4. In multi-hop forwarding paradigms for IoT, the operational lifetime is usually reduced, especially for nodes nearer to the sink, when high traffic passes through them.
5. Mobile sinks, although they offer an advantage, pose a problem in routing issues since they require continuously updating the network nodes, leading to unbalanced energy utilization and potential packet loss.
6. Various authors have identified the reasons for energy waste in communication, including idle listening, collisions, overhearing, control packet overhead, interference, redundant communications, distance, and the lack of clustering techniques.
7. Communication in general is an essential driver of the power demand, as well as processing the receipt and sending of data, which requires a significant amount of energy, and data transmissions need to be limited for energy efficiency
8. Transmission power control systems are challenging to design due to the diverse possible IoT scenarios and the dependence on distance and link quality.
9. Deploying transmission power control can also help maximize link quality by using the smallest power required to maintain a link.

10.48047/jocaaa.2024.32.01.66

10. Environmental factors such as the weather and other obstacles can cause signal quality variations and reliability between nodes.
11. Energy control remains crucial, as continuous activity can be triggered by factors such as sensing duration, bandwidth, and application field, among others, underscoring the need for longer network lifetimes.

To address these limitations, it is recommended that dynamic energy thresholds be implemented based on flow simulations in nodes, along with complementary measures to mitigate the impact on isolated nodes. To this end, a trade-off is envisioned between the following performance indexes: RE, Signal-to-Noise Ratio (SNR), and computational ability, considering real-time traffic dynamics, node mobility, energy efficiency, and adaptive clustering techniques. This feature eliminates the need to choose between energy consumption and packet reception, allowing for the improvement of latency-sensitive traffic by using a dynamic hop count. Additionally, all links must be accessible, which affects the reliability of the communication path and, consequently, the critical role of links in the total strength of the network.

3. Proposed Methodology

The network of the proposed work consists of N homogeneous SNs that interact with one another to sense their environment cooperatively. IoT nodes are deployed randomly and uniquely identified. Additionally, some nodes are equipped with a Global Positioning System (GPS), enabling them to determine their position within the network, referred to as Anchor Nodes (AN). All nodes possess identical energy levels, memory capacities, and processing power. In this network, the nodes play three primary roles: AN, CH, and Cluster Members (CMs).

3.1. Network Model

The network model outlines the essential assumptions and features of the wireless sensor network environment being considered. This includes factors such as the number of SNs, the deployment area, the distribution of nodes, whether randomized or planned, whether the nodes remain stationary or are mobile, the communication range for each node, and the capabilities of the nodes. Additionally, it typically defines the location and functions of the BS, where data is ultimately collected. Establishing an accurate network model is crucial as it lays the groundwork for designing and evaluating protocols, ensuring the proposed solutions align with the assumed conditions. An environmental scenario uses the sensor nodes collectively, grouping them into clusters. At any moment, one node can become the CH. The CHs gather data from the nodes and transmit it to the BS, as illustrated in Figure 1.

10.48047/jocaaa.2024.32.01.66

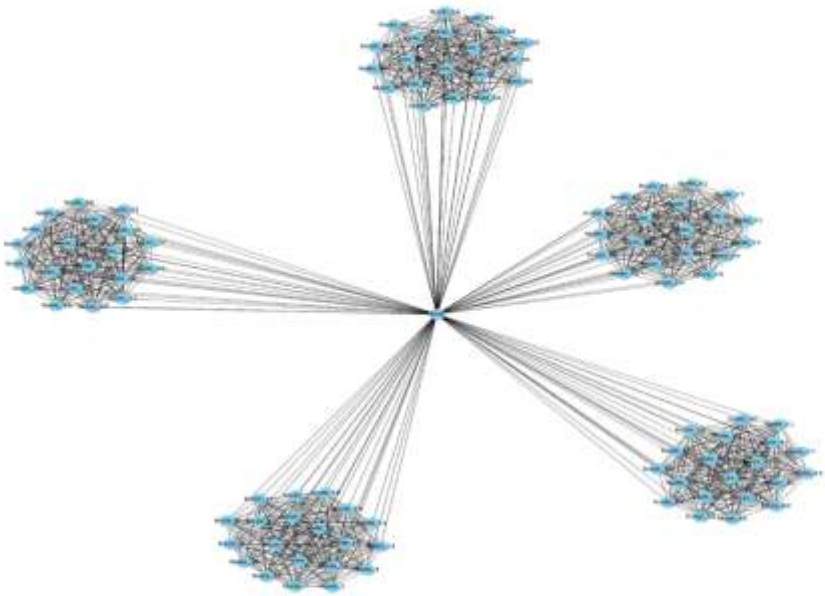


Figure 1. Network Model

For the network model, the following assumptions have been adopted,

- SNs are homogeneous and have identical resources.
- The SNs are uniformly distributed. They have the same data coverage range.
- Some nodes are designated AN with a GPS or other positioning device.
- Although all SNs are mobile before each round starts, they all remain stationary during the round. This means that the mobility of SNs would be before or after the round's beginning, moving at a certain velocity, and going to a random area.
- The nodes communicate in single-hop or multi-hop communication with the CH.
- According to the Zigbee MAC (ZMAC) time slot, SNs can exchange data directly with their CH or BS.
- Based on the received signal strength, the sensor node can measure the distance between itself and its neighboring nodes or the BS.
- CH communicates in single-hop or multi-hop communication by aggregating data with the BS.
- The BS is fixed in the outer region of the network.

The BS energy source, processing, and storage capabilities are unlimited, and the BS can cover the entire network region.

3.2. Energy Dissipation Model

The foremost challenge in designing IoT networks is conserving energy. Most nodes operate on small, limited-capacity batteries, making it difficult or impossible to recharge or replace them due to environmental constraints or the large number of nodes. Consequently, a node's lifespan, and thus the network's, depends on its energy usage. Studies show that the communication subsystem (radio transceiver) consumes the most energy, with data transmission and reception requiring more energy than sensing or computing. For example,

10.48047/jocaaa.2024.32.01.66

transmitting a single bit can consume the same amount of energy as executing thousands of instructions, making energy optimization crucial in IoT design. The energy model involves calculating the energy requirements of each node component, such as the radio, CPU, and sensors. By understanding the energy requirements of each node, the model helps estimate the total energy cost of the IoT network. Given the limited resources of SNs, prolonging the network's lifetime requires efficient energy use. However, the primary energy drain is from data transmission between SNs and the BS in an IoT setting. Therefore, it's essential to recognize the energy cost involved in data transfer, which rises with the size of data packets.

Equations (1) and (2) specify the first-order radio model for energy dissipation to transmit and receive an $L - bit$ packet across a distance of d, where d refers to the distance from the origin node to the destination node or the BS.

$$E_{TX}(L,d) = \begin{cases} L * E_{elec} + L * \epsilon_{fs} * d^2, d \le d_0 \\ L * E_{elec} + L * \epsilon_{mp} * d^4, d > d_0 \end{cases} \quad (1)$$

$$E_{RX}(L) = L * E_{elec} \quad (2)$$

Where E_{TX}, E_{RX} → Data transmission and reception energy, L → Length of a packet, E_{elec} → Energy spent powering the transmitter and receiver on and off, ϵ_{fs} → Free-space model, ϵ_{mp} → Multipath model, and d → Transmission distance are defined as $d(i,j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$. The threshold distance is represented by 'd_o' and is expressed as in Equation (3).

$$d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} = \sqrt{\frac{10\, pJ/bit/m^2}{0.0013\, pJ/bit/m^4}} = 87m \quad (3)$$

Data aggregation is a critical technique that enhances energy efficiency and extends network lifetime by reducing data redundancy. The main goal of data aggregation is to conserve energy. By removing redundant information and decreasing the number of packets transmitted across the network, particularly over long distances, aggregation significantly lowers the energy consumed by radio communication, which is the primary drain on sensor node batteries. This directly results in a longer operational lifetime for individual nodes and the network as a whole. Additional advantages include reduced network traffic and congestion, as well as improved bandwidth utilization.

The CH typically performs the data aggregation phase during the steady-state phase after receiving data packets from its members. Instead of forwarding all individual data packets, the CH processes the received data to produce a more concise summary or representation. This can involve averaging, finding minimum and maximum values, removing duplicate readings, or applying more complex fusion algorithms. The energy consumed by the CH for performing data aggregation of packets is defined in Equation (4).

$$E_{CDA} = L * Pkts * E_{DA} \quad (4)$$

10.48047/jocaaa.2024.32.01.66

Where L → Length of a packet, Pkts → Number of packets, and E_{DA} → Energy consumed for data aggregation.

The EC of a node and CH typically depends on the distance and the model used. Equation (5) gives the EC for non-CH nodes.

$$E_{nonCH} = (E_{RX} * L_{ctrl}) + ((E_{TX} * L_{data}) + \left(\epsilon_{fs} * L_{data} * d_{toCH}^{2}\right)) + E_{agg} + E_{SE} \quad (5)$$

Where E_{agg} → 0, E_{SE} → Node sensing energy. The energy consumption for CH nodes is given in Equation (6).

$$E_{CH} = (N * E_{RX} * L_{data}) + (\left(E_{TX} * L_{agg}\right) + (\epsilon_{mp} * L_{agg} * d_{toBS}^{4})) + E_{agg} + E_{SE} \quad (6)$$

Where L_{data} → Length of a data packet, L_{ctrl} → Length of an acknowledgement, L_{agg} → Length of aggregated packet, N → Number of CH member nodes, d_{toCH} → Distance to CH, and d_{toBS} → Distance to BS, E_{agg} → ($N_{members}$ x L_{data} + L_{sense}) x $E_{DAperbit}$, and L_{sense} → No. of bits sensed by a node.

3.3. Proposed Energy-Efficient GWO-GA Hybrid Technique

The LEACH protocol is valuable but faces challenges like uneven EC, early exhaustion of CHs, inefficient data aggregation, and poor scalability. To improve LEACH performance, the Energy-Efficient GWO-GA Hybrid Algorithm (EEGGHA) is introduced to overcome these limitations. Clustering in LEACH enhances network scalability, manageability, and energy efficiency by reducing the number of radio transmissions. SNs are grouped into clusters, each led by a CH that coordinates and aggregates data, differing from flat architectures where nodes have similar roles. In EEGGHA, elected CHs broadcast formation details; a 1-hop neighbor node assesses its distance to multiple CHs from signal strength and joins the closest cluster. Data transmission is scheduled using ZMAC to minimize collisions, enhance connectivity, and reduce packet loss. Nodes share information within two hops, and 2-hop nodes send data to 1-hop nodes at scheduled times to avoid conflicts. ZMAC enables efficient energy use by reducing unnecessary listening compared to Time Division Multiple Access (TDMA), as it limits the number of monitored data packets within time slots, thereby boosting energy efficiency. This paper introduces EEGGHA for optimizing energy-efficient paths, mitigating LEACH's weaknesses in IoT networks.

3.3.1. Mobility

Mobility introduces dynamism within the network where sensor nodes, specialized relay nodes, or data sinks change their physical locations over time. Sink mobility, sometimes used to balance energy consumption near the sink, requires adaptive routing strategies. Mobility can manifest in various forms,

1. Mobile Sensors: Nodes themselves move, such as wearable sensors tracking human activity or health parameters, sensors attached to animals for habitat monitoring, or nodes deployed on mobile robots.

10.48047/jocaaa.2024.32.01.66

2. Mobile Relays: Dedicated nodes that move within the network to assist in data forwarding, potentially bridging disconnected network segments or optimizing paths dynamically. These relays typically do not sense data but move strategically to facilitate communication.
3. Mobile Sinks: A BS or specialized data collector moves through the sensing field to gather data from static or mobile sensor nodes.

The introduction of mobility has a profound and multifaceted impact on the design and performance of IoT systems. On the one hand, mobility offers several potential benefits. It can significantly increase the effective coverage area of the network, as mobile nodes can explore larger regions than static deployments. Mobile sinks, in particular, are a key strategy for energy balancing and mitigating the "energy hole" or "hot spot" problem, where nodes closest to a static sink deplete their energy much faster due to relaying heavy traffic. By relocating the sink, the high-traffic zone is shifted, distributing the energy burden more evenly across the network and potentially extending its overall lifetime. Mobility can also enhance channel capacity, enabling novel applications like target tracking, environmental sampling with robots, or dynamic surveillance. The Relative Position Update (RPU) with constant velocity for $node_i$ is given by,

$$\begin{pmatrix} P_{x,i}(t+\Delta t) = P_{x,i}(t) + V_{x,i} * \Delta t \\ P_{y,i}(t+\Delta t) = P_{y,i}(t) + V_{y,i} * \Delta t \end{pmatrix} \tag{7}$$

Where the velocity components using a random angle A are given as,

$$\begin{pmatrix} V_{x,i} = S_i * \cos(A) \\ V_{y,i} = S_i * \sin(A) \end{pmatrix} \tag{8}$$

When choosing a new path segment, the speed magnitude S_i for $node_i$ is uniformly selected from the range [S_{min}, S_{max}], given as,

$$S_i = S_{min} + rand() * (S_{max} - S_{min}) \tag{9}$$

Where $P_{x,i}(t)$, $P_{y,i}(t)$ → Position of $node_i$ at time t, $V_{x,i}$, $V_{y,i}$ → Velocity of $node_i$ at time t, S_i → Speed magnitude for $node_i$, S_{max} → Maximum speed of a node, S_{min} → Minimum speed of a node, Δt → Time step duration, and rand() → A function generating a uniform random number between [0, 1].

3.3.2. Localization with GWO

The GWO, a part of swarm intelligence techniques, emulates the social structure and hunting strategies of a grey wolf pack. It categorizes solutions into alpha, beta, delta, or omega wolves, reflecting a structured hierarchical model. The algorithm follows three phases inspired by wolves' hunting: exploration (scouting), exploitation (surrounding and capturing prey), and an adjustment phase based on the positions of the alpha, beta, delta, and omega wolves. GWO is particularly effective in solving node localization problems by notably reducing the discrepancy between estimated and actual node positions. It begins with the random positioning of wolves, and in each iteration, fitness is evaluated using an objective function designed to

10.48047/jocaaa.2024.32.01.66

minimize error. Wolf positions are adjusted to follow the best-performing leaders, alpha, beta, and delta. This cycle repeats until certain stopping conditions are met, and the alpha wolf's final position estimates the node location. This involves determining unknown sensor positions using the fixed coordinates and distance data of anchor nodes, obtained via techniques.

The goal of the GWO-based localization method usually focuses on reducing the localization error, which is often expressed as the total of squared differences between the observed distances (obtained from RSSI) and the predicted distances (computed using the Euclidean distance formula based on the wolf's current position estimate relative to the locations of the anchor nodes). For an unidentified node i with estimated coordinates (x, y) and m anchor nodes that have known coordinates and measured distances, a typical objective function to optimize is defined in Equation (10).

$$f(x,y) = \sum_{j=1}^{m} \left(\sqrt{\left(x - x_j\right)^2 + \left(y - y_j\right)^2} - d_{ij}^{meas} \right)^2 \tag{10}$$

Where x, y → Estimated position of unknown node, x_j, y_j → Anchors with known positions, m → Total anchors, and d_{ij}^{meas} → Noisy distance estimates.

This approach adapts GWO to find the coordinates (x, y) of an unknown node, minimizing the difference between measured distances to anchors and calculated distances based on the estimated coordinates.

3.3.3. Cluster Construction

The cluster formation phase is a crucial stage in clustering protocols. During this phase, groups are formed within the IoT network, and the network organizes itself into clusters. This phase also includes CH election and cluster members' association to a cluster based on the neighbor's node degree and the average residual energy. Forming an optimal, energy-efficient cluster-head election involves a multi-step process that requires considering the specific characteristics and constraints of IoT devices. A deliberate strategy is necessary to develop an optimal formula for CH election in a network that minimizes energy consumption and maximizes residual energy. This typically involves selecting specific nodes to act as CHs based on criteria like residual energy, node degree, or location. Once CHs are selected, non-CH nodes resolve which cluster to join, usually based on proximity signal strength or distance to a CH. The goal is to create a hierarchical structure where regular nodes primarily communicate with their local CH, thereby reducing long-distance transmissions and conserving energy.

I. Setup Phase

The first round divides the network into k out of n nodes, a predefined number of clusters. In this round, the nearest nodes to the BS are selected as CH based on the estimated distance. The setup phase often encompasses the cluster formation phase, but can also include subsequent organizational tasks before the network begins its primary data gathering and transmission routine. Besides forming clusters and selecting CHs, the setup phase may involve creating communication schedules within each cluster to avoid collisions, disseminating CH

10.48047/jocaaa.2024.32.01.66

information to member nodes, and establishing routing paths between CHs and the base station. This phase establishes the network structure and operational parameters necessary for the subsequent steady-state operation. The initial energy spent during cluster formation (like advertisements, join requests, and scheduling) is given in Equation (8),

$$E_{Setup} = k * E_{TX}(CH_{advt}, d_{max}) + N * E_{RX}(CH_{advt}) + (N-k) * [E_{TX}\left(CH_{join}, d_{avg2CH}\right) + E_{RX}(CH_{join})] + k * E_{TX}(CH_{sch}, d_{max-intra}) \quad (11)$$

Where k → Number of CHs in the network, E_{TX}, E_{RX} → Data transmission and reception energy, CH_{advt}, CH_{join}, CH_{sch} → Cluster control packets for advertisement, join, and schedule, d_{max} → Broadcast range, d_{avg2CH} → Average distance to CH, and $d_{max\text{-}intra}$ → The maximum intra-cluster distance.

The number of clusters k in Equation (8) can be optimized to minimize the node energy consumption per round, which is defined in Equation (9).

$$k_{opt} = \sqrt{\frac{N * \epsilon_{fs} * A}{2\pi * \epsilon_{mp} * d_{CH2BS}^2}} \quad (12)$$

Where N → Quantity of nodes in the network, A → Uniformly distributed area, and d^2_{CH2BS} → Distance from CH to BS.

For the term d_{CH2BS}^2, use d^2 instead of d^4 because the proposed technique breaks long-distance CH to BS transmissions into shorter hops (multi-hop), resulting in energy conservation. Thus, using k_{opt}, Equation (11) is modified into Equation (13),

$$E_{Setup} = k_{opt} * E_{TX}(CH_{advt}, d_{max}) + N * E_{RX}(CH_{advt}) + \left(N - k_{opt}\right) * [E_{TX}\left(CH_{join}, d_{avg2CH}\right) + E_{RX}(CH_{join})] + k_{opt} * E_{TX}(CH_{sch}, d_{max-intra}) \quad (13)$$

Once for the current round CHs are selected, they relay their announcement details to the member nodes within their clusters. The sensing nodes evaluate the strength of the incoming request message and decide which CHs they want to join. The CH then sends ZMAC schedules, enabling the member nodes to transmit their data in separate time slots to avoid data collisions. This procedure continues for each round until all nodes in the network have exhausted their energy.

II. Steady-State Phase

The second phase is the main operational phase of a clustered network, following the setup phase. During this period, SNs actively monitor the environment, collect data, and transmit the data to their respective CHs. The CHs then typically perform data aggregation or fusion to reduce redundancy before forwarding the processed data towards the BS, possibly via other CHs in a multi-hop manner. This phase usually constitutes the longest part of the network's operational lifetime and is where the most valuable data is gathered. Energy efficiency during this phase is critical to maximizing network longevity. The energy spent per

10.48047/jocaaa.2024.32.01.66

round for sensing data, intra-cluster data communication, data aggregation, and inter-cluster data communication is specified by Equation (14),

$$E_{Steady} = N * E_{sense} + \sum_{c=1}^{k}\left(\sum_{i \in Members(c)} E_{SH}\big(L, d(i, CH_c)\big)\right) + \sum_{c=1}^{k}\big(\eta_c * E_{RX}(L) + E_{DA}(\eta_c, L)\big) + \sum_{c=1}^{k} E_{MH}\left(L_{agg}, Path(CH_c, BS)\right) \quad (14)$$

Where N → Number of nodes in the network, E_{sense} → Energy for sensing node per round, L → Length of a packet, η_c → Average nodes per cluster, E_{SH} → Intra-cluster energy defined in Equation (10), E_{MH} → Inter-cluster energy defined in Equation (11), E_{TX}, E_{RX} → Data transmission and reception energy, CH_c → Distance to CH, Path → Denotes the path from CH_1 → CH_2 → CH_3→ ... → CH_n → BS, E_{DA} → Energy consumed for data aggregation, and L_{agg} → Aggregated packet size.

When the distance between SNs and BS is minimal, energy dissipation resembles the behavior of the free space model. The multipath fading model is used for long-distance data transmission from many sensor nodes to a limited number of BS. A significant quantity of energy may be conserved if the transmission distance is within the range. Using equation (1), how much energy a single-hop communication (E_{SH}) requires to send data from a member node to the CH is calculated as given in Equation (15).

$$E_{SH}(L, d) = E_{TX}(L, d) = L * E_{elec} + L * \epsilon_{amp} * d^{\delta} \quad (15)$$

Where ϵ_{amp} → ϵ_{fs} if $d \le d_0$ or ϵ_{mp} if $d > d_0$, and δ → path-loss exponent (either 2 or 4). The energy needed for multi-hop communication (E_{MH}) between the CHs and BS to send aggregated data is defined in Equation (16),

$$E_{MH}\big(L_{agg}, Path\big) = E_{DA} + \sum_{i=0}^{m}\left(E_{TX}(L_{agg}, d(CH_i, NextHop_{i+1})) + E_{RX}(L_{agg})\right) \quad (16)$$

Where Path → Denotes the path from CH_1 → CH_2 → CH_3→ ... → CH_n → BS, and $NextHop_{i+1}$ → Denotes next hop to CH or BS.

III. Re-Clustering

Re-clustering involves reorganizing network clusters to adapt to changing conditions and ensure efficiency over time. The process involves rotating the role of the CH, which is more energy-intensive due to its tasks of data aggregation and transmission. To prevent rapid energy depletion in a single node, CHs are rotated based on energy thresholds or the current load, thereby maintaining overall network longevity by sharing the energy burden among nodes. This rotation strategy, usually conducted during the setup of each round, considers residual energy and load when choosing a new CH. However, the strategy needs to balance energy consumption against the overhead caused by frequent re-clustering. Frequent CH rotation adapts quickly to energy changes but increases setup overhead, while infrequent

10.48047/jocaaa.2024.32.01.66

rotation risks premature CH failure. Therefore, optimizing CH rotation by considering current energy levels or communication load, rather than strictly adhering to scheduled intervals, aims to enhance network sustainability.

Re-clustering is initiated in response to specific events. Common events include a CH's RE falling below a predefined threshold, node failure or mobility, violation of QoS requirements, or perhaps detection of network partitioning. This approach is more adaptive to unpredictable changes. The proposed work triggers the re-clustering event when RE falls below a threshold. The Fitness Function (F_{CH}) for high RE and potentially penalizing recently selected CH is defined in Equation (17),

$$F_{CH}(i) = \omega_1 * E_{RE}(i) - \omega_2 * CH_{TimeLastServed}(i) \tag{17}$$

Where ω_1, ω_2 → Weights for normalization between [0, 1], E_{RE} → Residual energy of a node, and $CH_{TimeLastServed}$ → CH time since last served. Using Equation (17), the next CH is selected in rotation as defined in Equation (18),

$$NextCH = \underset{i \in ClusterMembers, i \neq currentCH}{\operatorname{argmax}} \{F_{CH}(i)\} \tag{18}$$

The entire network participates in the re-clustering process, typically involving CH election across all nodes and subsequent cluster formation. This allows for network-wide optimization and load balancing.

3.3.4. Intra-Cluster and Inter-Cluster Communication Phase

Data transmission and management are essential for reliably delivering sensed information within network constraints. This process involves handling data packets and utilizing techniques such as data aggregation to enhance resource efficiency. During data packet transfer, sensed data is transmitted from SNs to the destination, typically a BS, via multi-hop communication involving relay nodes. The network's transport layer is key, providing control over data flow and ensuring reliability.

Applications require reliable data transport, but packet loss is common due to issues such as wireless link problems, node failures, or network congestion. Recovery mechanisms are necessary to handle such losses. Energy efficiency is critical; packet loss and retransmissions waste energy. Congestion control prevents buffer overflows from excessive traffic. Using hop-by-hop recovery, where losses are detected and corrected between adjacent nodes, is often more energy-efficient than end-to-end recovery, as it focuses recovery efforts locally. Equation (19) defines the distance between nodes i → j belonging to the same cluster c, which refers to the distance between a member node i → CH_c.

$$d_{intra-c}(i, CH_c) = d(i, CH_c) \tag{19}$$

Using Equation (19), the average intra-node distance of a cluster c is defined in Equation (20).

$$d_{intra-c}(c) = \frac{1}{n_c} \sum_{i \in Members(c)} d(i, CH_c) \tag{20}$$

10.48047/jocaaa.2024.32.01.66

The distance between two different cluster heads or to the BS is defined in Equation (21).

$$d_{inter-c}(CH_i, CH_j) = d(CH_i, CH_j)\ and\ d_{inter-BS}(CH_i, BS) = d(CH_i, BS) \quad (21)$$

This stage refers explicitly to the timeframe during which sensor nodes actively relay their collected data packets to their assigned CH, after which the CHs send the aggregated data packets to the BS. The protocols governing this transmission may incorporate specific Medium Access Control (MAC) strategies, such as ZMAC, to organize transmissions within a cluster and prevent collisions. Practical and dependable data packet transmission is essential for the network's operation. The adaptive intra-cluster communication cost (C_{intra}) within a cluster, typically from member nodes to the CH, is given in Equation (22).

$$C_{intra}(i,t) = \omega_E * E_{TX}\big(L(i,t), d(i, CH_c)\big) + \omega_R \frac{1}{RP(i,t)} + \omega_C * CP(CH_c, t) \quad (22)$$

Where E_{TX} → Data transmission energy, RP → Importance of a node "i" at time "t" and penalty based on previous readings, prediction error, or priority, CP → Congestion at CH and its penalty normalized between [0, 1], and ω_E, ω_R, ω_C → Positive weights in the range [0, 1].

The node i decides to transmit only if $C_{intra} < Threshold_{TX}$ to minimize this cost. This promotes energy conservation by possibly decreasing packet size depending on energy availability and data redundancy. It emphasizes transmission based on data importance, ensuring that vital information is transmitted even if the energy expenditure is slightly higher, while limiting the transmission of duplicate data. It considers the network status through the congestion factor, which may lead nodes to reduce their transmission power/rate or back off during peak times to enhance overall cluster efficiency and reliability. This enables more intelligent data reporting within the cluster, adjusting to both the state of the nodes and the network conditions. By reducing this cost function, nodes strive to balance energy efficiency, information significance, and network stability, enhancing network longevity.

Data communication between clusters, typically CH-to-CH relaying or CH-to-BS, focuses on the energy cost of transmissions and sometimes considers optimal path selection based on minimum energy and link reliability. Equation (23) defines the adaptive reliable link cost (Cinter).

$$C_{inter}(i,j) = \frac{E_{TX}\left(L_{agg}, d(i,j)\right)}{\max(PRR(i,j) - PRR_{min})} \quad (23)$$

Where E_{TX} → Data transmission energy, PRR(i, j) → Packet Reception Ratio for the link (i, j), PRR ∈ [0, 1], PRR_{min} → Acceptable minimum PRR threshold, and d(i, j) → Transmission distance between two CHs.

The proposed technique selects the best neighbor CH to act as a relay node if a multi-hop transmission is chosen in inter-cluster communication. This ensures a balanced load, resulting in energy conservation. It selects a relay CH_j from neighbors $N(CH_i)$, maximizing the cost function given in Equation (24).

10.48047/jocaaa.2024.32.01.66

$$C_{relay}(j) = \omega_1 * \frac{E_{RE}(j)}{E_{init}(j)} + \omega_2 * \left(1 - \frac{d(i,j)}{d_{max}}\right) + \omega_3 * \left(1 - \frac{d(j,BS)}{d_{max}}\right) - \omega_4 * \frac{TimesRelayed(j)}{MaxRelays} \quad (24)$$

Where ω_1, ω_2, ω_3 ,ω_4 → Positive weights in the range [0, 1] summing to 1, E_{RE}, E_{init} → Current residual energy and initial energy of a node, d(i, j) → Transmission distance between two CHs, d_{max} → Maximum network dimension, TimesRelayed(j) → Count of recent relay tasks for node "j", MaxRelays → Maximum relay nodes, and d(j, BS) → Transmission distance defined as $d(j,BS) = \sqrt{(x_{BS} - x_j)^2 + (y_{BS} - y_j)^2}$.

This cost function balances multiple relay characteristics and prioritizes nodes with ample energy to sustain the relay task (receiving and transmitting). Optimizing this function leads to energy-efficient paths while preventing premature failure of popular relay nodes near the BS. Rotation enhances network lifetime by distributing the relaying load.

3.3.5. Genetic Programming in the Proposed Technique

Genetic programming utilizes random search and optimization, guided by "Survival of the Fittest," where only the most robust solutions endure. GAs evaluates solution quality through a fitness function, which influences the generation of offspring. This process iterates to attain near-optimal solutions swiftly. Initially, GAs creates populations with uniform chromosome lengths, and the fitness function assesses how closely the solutions approach the ideal. Recombination involves the crossing of two chromosomes to produce offspring that resemble their parents. Mutations occur after crossover, introducing genetic diversity and enhancing convergence. Following mutation, new-generation chromosomes are selected, replacing underperforming ones with elite predecessors to ensure fitness. The algorithm concludes upon achieving elitism. GA performance depends on several factors, including population size, fitness function, crossover and mutation methods, and replacement strategy. Ultimately, GAs aim to evolve new generations that surpass prior ones through selection, crossover, and mutation, ensuring only the best-adapted individuals thrive.

A. Chromosome Representation

GAs generates high-quality solutions through operators such as crossover, mutation, and selection. The initial step involves establishing a genetic pool of randomly chosen individuals for problem-solving. Evaluate each chromosome's performance, then repeatedly form new populations via the same procedure. Crossover serves as a critical genetic operator to develop new generations. In an IoT network, the quantity of hops a packet takes to reach the BS depends on the sensor node's location. Network nodes act as individual genes, and a chromosome represents a specific path as a sequence of nodes. The chromosome's length corresponds to the quantity of relay nodes. Each cell within a chromosome signifies a unique relay node, which functions as a data transmitter. The cell value indicates the relay node receiving data from its source node. As the BS only receives data, it need not be depicted as a source node on the chromosome.

10.48047/jocaaa.2024.32.01.66

Each node in the network is optimized for its path in the proposed technique, and the chromosome length changes depending on the node's position. A suitable representation for encoding paths is a next-hop array. For instance, a chromosome C for the path $N1 \rightarrow N2 \rightarrow CH4 \rightarrow CH3 \rightarrow BS$ is represented as in Equation (25).

$$Chromosome\ (C) = [1, 2, 4, 3, 0] \tag{25}$$

Where "0" represents the BS ID. Chromosome encoding is based not on binary 0s and 1s but on node or CH IDs. Accordingly, in a network, each gene stands in for the neighboring gene in the following hop.

B. Selection

Selecting group members for further study can enhance the overall quality of that population. To choose the ideal individuals to serve as parents in subsequent generations through crossing and mutation, this proposed work employs a tournament selection procedure, along with the elitist method, to identify the best chromosome. Each top chromosome is assigned a distance and rank parameter. The fitness value of the chromosome influences the likelihood of being selected, with higher chances for those with greater values. The fitness of the population's members determines their placement on a roulette wheel with varying diameters. The tournament method begins with two randomly selected participants, who use a comparison operator to determine the winner. The total fitness of the population, the selection probability of each individual, and the cumulative probability of each individual are provided in Equation (26).

$$P_{cum}(C_i) = \sum_{j} 1^{i} Prob\left(\frac{Fitness(C_i)}{\sum_{k=1}^{N} Fitness(C_k)}\right) \tag{26}$$

Where Fitness(C) → Fitness of individuals, and Prob → Probability in the range [0, 1].

C. Crossover

Recombination of component material occurs as a result of mating in this process. The chromosomal selection procedure influences the outcomes of the crossover. One binary genetic operator that can be utilized for a pair of parents is the crossover operator. The crossover is executed to generate new offspring from the selected parents. The k-point crossover (k = 1, 2, or 3) selected randomly for each generation is chosen. Figure 2 illustrates an example of a 2-point crossover involving two parent chromosomes, Parent A and Parent B, within a network. Two random numbers, r1 and r2 (where r1 ≠ r2), are selected such that r1 and r2 belong to the set {1…n-1} to establish the crossover points. In this case, r1 = 3 and r2 = 2 indicate the crossover points (blue column).

10.48047/jocaaa.2024.32.01.66

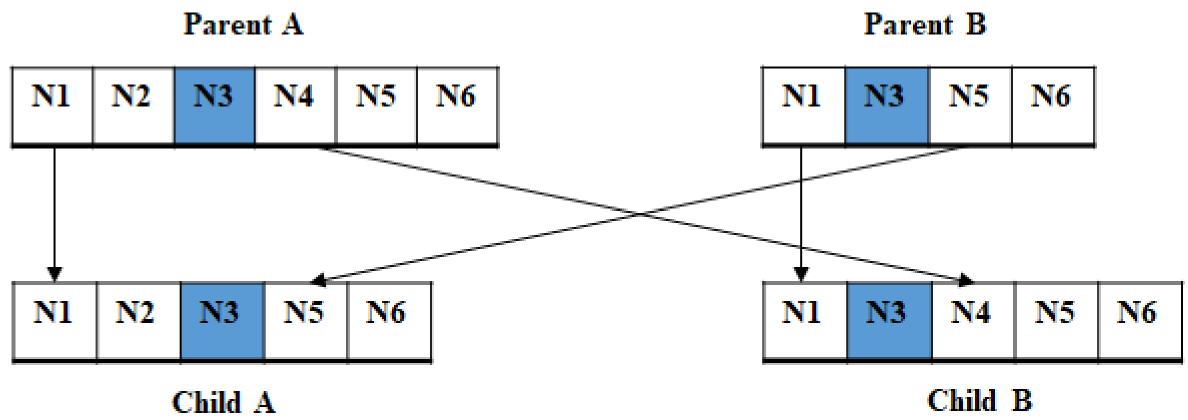


Figure 2. 2-point Crossover

Child C and Child D are formed when a crossover occurs, and the gene values of the parents in the crossover regions r1 and r2 are flipped, respectively. This crossover technique ensures that both offspring are viable solutions to the routing problem. The crossover method with two random points, p1 and p2, is presented in Equation (27).

$$P_c = 1 \leq p_1 < p_2 < L \tag{27}$$

Where L is the chromosome length, determining the crossover rate requires careful planning due to its significant influence on GA performance.

D. Mutation

The mutation rate, like the crossover, determines the frequency of mutation. A randomly chosen gene is altered after the crossover phase to promote fitness in GA. Identify the crucial node as the mutation candidate in the proposed GA. To know how long the network will last, look at the energy-hungry node for sending and receiving data. Concentrating mutation efforts on the crucial node may lower energy dissipation and boost the network's lifetime. Two techniques decrease critical node energy loss. In the first situation, the essential node must transfer less data across a shorter distance; in the second, it must send fewer data overall.

i) By altering the critical node's destination to a randomly chosen node that is suitable and nearer to the critical node, or
ii) Divert incoming stream from the critical node.

Figures 3(a) and 3(b) illustrate the changes in the equivalent chromosome representations, respectively.

As illustrated in Figure 3(a), changing the node must be performed in a way that d (N5, N6) < d (N5, N4) and d (N6, N7) < d (N5, N7), where d (x, y) is the Euclidean distance from node x to node y. Similarly, in Figure 3(b), reduce the load on the critical node N5 by diverting the traffic from node N2 to node N6 instead of node N5. The alternate destination node N6 should be selected such that d (N6, N7) < d (N2, N7) and N6 lies within the transmission range of N2.

10.48047/jocaaa.2024.32.01.66

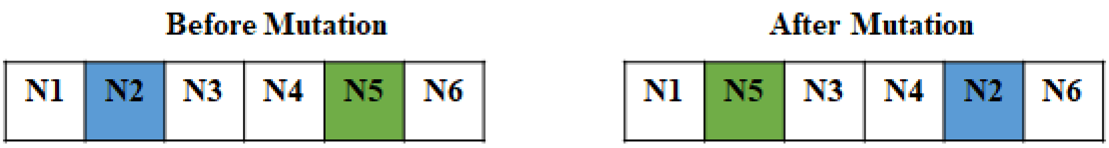


Figure 3(a). Chromosome Representation After the First Mutation

Figure 3(b). Chromosome Representation After the Second Mutation

Similarly, the frequency of mutations is methodically regulated and closely linked to the rate of crossings. While a high mutation rate can threaten population stability, a low mutation rate may lead the GA to converge quickly before identifying the optimal result.

E. Elitism

In elitism, top individuals are selected based on fitness. These individuals are directly carried forward to the next generation without any modification. When the prerequisites for halting are satisfied, the GA will cease execution. Although the GA cannot guarantee that it will discover the global optimal solution, it may still be able to find a suitable solution to a complex issue within a reasonable timeframe. An appropriate threshold is determined,

1. When an acceptable solution is identified that meets the bare basic requirements,
2. When the generation count reaches a user-defined maximum,
3. When the population's average fitness reaches at least 95% of the best fitness, this is known as "Convergence."
4. Any permutation of the above three policies.

Increasing the mutation rate permits the introduction of new genetic variations, thereby meeting the second convergence criterion. The halting criteria should be well-considered to arrive at a better answer quickly.

After the specified number of generations, the activities mentioned above are terminated. Each iteration compares the current fitness value to the value from the prior iteration. The chromosomes are revised appropriately. Afterward, CHs are chosen based on the highest fitness chromosomes or nodes. The most significant value of the fitness function ensures the optimal CH selection, characterized by high residual energy and the shortest communicative distance from the BS.

3.3.6. Fitness Function

The fitness function considers various performance criteria to either maximize or minimize an expression. It defines an individual's fitness by discussing multiple fitness criteria. The current value of the fitness parameter depends on several important factors, which is why

10.48047/jocaaa.2024.32.01.66

it is closely examined. It is worth noting that the optimization level increases as the parameter's relevance grows. The primary goals of the fitness parameters in this context are to reduce energy consumption and maximize network longevity. By breaking down each parameter into its explanation, the fitness function can identify the best profile node to serve as the CH, significantly influencing the process. Using this technique, achieves an energy-efficient choice of CH.

When using the weighted sum average technique, the previously mentioned network functions are distinct. Thus, all the above criteria are combined into the first objective metric, a network path function, f_1', as shown in Equation (28).

$$f_1{}' = \omega_1 * \left(\frac{\overline{E_{RE-CH}}}{E_{init}}\right) + \omega_2 * \left(1 - \frac{\overline{C_{intra}}}{d_{max}}\right) + \omega_3 * \left(1 - \frac{\overline{C_{inter}}}{d_{max}}\right) + \omega_4 * \left(1 - \frac{\overline{L_{CH}}}{L_{max}}\right) + \omega_5 * \left(1 - \frac{\left|k - k_{opt}\right|}{N/2}\right) \tag{28}$$

Where E_{RE-CH} → Average RE of k CHs, C_{intra} → Average distance of CMs to CH, C_{inter} → Average distance of k CHs to BS, L_{CH}, L_{max} → Average load of CH and possible maximum load, k → Number of clusters in the current round, k_{opt} → Optimal number of clusters, d_{max} → Possible maximum distance in the network, N → Quantity of nodes in the network, and ω_1, ω_2, ω_3, ω_4, ω_5 → Positive weights in the range [0, 1] summing to 1.

Use $[\omega_1, \omega_2, \omega_3, \omega_4, \omega_5] = [0.25, 0.25, 0.15, 0.15, 0.20]$. These values can be tweaked according to the network topology to yield an optimal solution. The second objective metric defined by the proposed technique is the average PDR in the network. The PDR and average PDR of a path are defined in Equations (29) and (30).

$$PDR = \begin{cases} 1, when\ RSSI > -86 \\ 1 - \dfrac{1}{1 + 223.5424 * e^{2.1771*RSSI+198.4593}}, when -96 < RSSI \leq -86 \\ 0, when\ RSSI \leq -96 \end{cases} \tag{29}$$

$$f_2{}' = PDR_{avg}(Path_i) \tag{30}$$

The third objective metric estimates the network lifespan. It estimates the minimum energy remaining on any CH after one round of transmitting and the intermediate relaying node derived from Equation (24).

$$f_3{}' = \sum_{i=1}^{N_{active}(t)} E_{RE}(i, t) \tag{31}$$

The combined multi-objective fitness function is defined in Equation (32).

$$F = \alpha_1 * f_1{}' + \alpha_2 * f_2{}' + \alpha_3 * f_3{}' \tag{32}$$

10.48047/jocaaa.2024.32.01.66

Where f_1', f_2', and f_3' are the normalized values of the objective metrics. α_1, α_2, and α_3 are the weights in the range [0, 1] summing to 1, reflecting the priority of each objective. The higher F designates a better path in the network.

3.3.7. Optimal Path Selection in Proposed EEGGHA

The goal is to identify the optimal path from a source node to a destination node based on the cost metric, typically by minimizing the network's total energy consumption, maximizing PDR, and extending the network lifespan. The optimal path cost metric is derived from Equation (32) and defined in Equation (33).

$$Cost(Optimal\ Path) = \max_{i \in \{1:n\}} F(i) \tag{33}$$

By appropriately defining the weights, identify the path that optimizes this cost metric, thereby minimizing energy consumption, maximizing PDR, and extending network lifespan.

3.3.8. Energy Consumption of the Proposed EEGGHA

Below are the energy consumption calculations (E) for the proposed technique at various levels, specifically focusing on a single round. Equations (1) and (2) outline the energy consumption of a node, while Equation (34) details the energy consumption of a CM.

$$E_{member}(i) = E_{Sense} + E_{TX}\big(L, d(i, CH_c)\big) \tag{34}$$

The energy consumption of a cluster per round is defined in Equation (35).

$$E_{cluster}(c) = E_{CH}(c) + \sum_{i \in Members(c)} E_{member}(i) \tag{35}$$

The term CH_c with n_c members from Equation (35) is defined in Equation (36).

$$E_{CH}(c) = E_{Sense} + n_c * E_{RX}(L) + E_{TX}\big(L_{agg}, d_{CH2NextHop}\big) + (n_c * L) * E_{Proc} \tag{36}$$

Where E_{Sense} → Node sensing energy, d → Distance to next hop relay CH or BS, and E_{Proc} → Energy spent for processing data.

Equation (37) represents the energy consumed by a CH acting as a relay for data from other clusters, receiving packets from other nodes or CHs, potentially processing or re-aggregating them, and transmitting them to another relay or BS.

$$E_{relay}(j) = m * E_{RX}\big(L_{relay}\big) + \big(m * L_{relay}\big) * E_{Proc} + m * E_{TX}\Big(L_{relay}, d(j, NextHop)\Big) \tag{37}$$

Where j → Node j, and m →Number of packets.

An anchor node is used for localization and periodically broadcasts a beacon signal containing its position information. The energy consumed by an anchor node in one round is given in Equation (38).

10.48047/jocaaa.2024.32.01.66

$$E_{Anchor}(i) = E_{TX}(L_{beacon}, d_{broadcast}) \tag{38}$$

Where beacon → Beacon signal from the anchor node, and broadcast → Broadcast range of the anchor node.

The consumed energy by all nodes in the network for one round is given in Equation (39).

$$E_{Round}(r) = \sum_{r=1}^{n}\left(\sum_{i=1}^{N} E_{node}(i, r)\right) \tag{39}$$

Where $E_{node}(i, r)$ → The energy consumed by CM, CH, relay, anchor, idle, or sleeping, n → Total number of iterations, N → Quantity of nodes in the network, and $E_{node} = E_{sleep}$ → Energy is often negligible. The cumulative EC from round 1 to round n is defined in Equation (40).

$$E_{Total}(n) = \sum_{i=1}^{n} E_{Round}\,(i) \tag{40}$$

$E_{Round}(i)$ is the energy consumed for a single round, and $E_{Total}(n)$ is the cumulative energy consumed in the network. The cumulative RE of all the active nodes in the network at a given time "t" is defined in Equation (41).

$$E_{RENet}(t) = \sum_{i=1}^{N_{active}(t)} E_{RE}(i, t) \tag{41}$$

Where N_{active} → Nodes active in the network, E_{RE} → Residual energy of a node. The nodes may be ordinary, ANs, CHs, or intermediate relaying nodes.

3.3.9. Pseudocode of the Proposed Technique EEGGHA

Below are detailed instructions for generating an optimized hybrid GA global solution used in the proposed work, EEGGHA. First, apply the GWO algorithm to find node localization and optimal placement.

```
Procedure Localization_GWO()
Begin
Input: Anchor_locations ← A[j], Measured_distance ← d_m[j], Search_range ← {min, max}, N, MaxIter
Output: X_alpha ← Estimated position of the target node
Generate an initial population of wolves X_i, where i = 1, …, N
Initialize t = 0
Compute the fitness f(X_i) for all wolves using Equation (10)
IF Fitness is best then
Find X_alpha, X_beta, X_delta
END IF
WHILE t < MaxIter DO
Calculate 'a'
FOR each wolf I = 1: N DO
FOR each dimension d = 1 to dimension DO // (i.e., dimension = 2 for 2D)
(A1, C1) ← 'a', (A2, C2) ← 'a', (A3, C3) ← 'a'
```

10.48047/jocaaa.2024.32.01.66

```
    Compute D_alpha,d, D_beta,d, D_delta,d
    Calculate X1,d, X2,d, X3,d
    X_i,d(t+1) ← (X1,d +  X2,d + X3,d) / 3
    END FOR
    Apply boundary checks on X_i(t+1)
    END FOR
    Compute the fitness f(X_i(t+1)) for all wolves using Equation (10)
    IF new_Fitness is best then
    Find X_alpha, X_beta, X_delta
    END IF
    t ← t + 1
    END WHILE
    RETURN X_alpha // (the location of the alpha  wolf)
End
```

The GA algorithm is now used to find the energy-efficient and optimal solution to reach the BS from the source, which maximizes RE and PDR and minimizes energy consumption.

```
Procedure hybrid_GA()
n: total number of nodes
m1, m2: number of nodes in the first and second generation
A []: an array that contains all the possible paths
func (): objective function with constraints to be satisfied
S: a set of constraints to be satisfied, i.e., energy-aware optimum path among the available paths
Gen: The population generation counter
Begin
    X ← {1,2,3… n}
    Gen ← 0
    WHILE Gen < MaxGenerations DO
    Y ← {x1, x2, x3, …, xn}
    Gen ← Gen + 1
    E ← check the Elitism criteria
    Selection ← Select N-E parents using Equation (26)
    Crossover ← Perform two-point crossover using Equation (27)
    Offspring ← Perform Mutation
    Old_Population ← New_Population
    F ← Calculate fitness using Equation (38)
    Evaluate the Termination condition
    END WHILE
    P_opt ← max {F}
    RETURN P_opt
End
```

3.3.10. Mathematical Proof of the Proposed EEGGHA

The mathematical proof of the proposed technique is presented below. A fundamental principle of GA is that each successive generation should be superior to the one that came before it. In the first stage, preliminary candidates for potential solutions are generated, and efficiency comparisons are conducted. A new population of candidate solutions is produced using the three fundamental evolutionary operators: selection, crossover, and mutation. Only the fittest individuals in the population are expected to survive this cycle of reproduction and extinction. The GA algorithm's five fundamental operations, initial population, fitness function, selection, crossover, and mutation, are applied iteratively. Figure 4 illustrates a scenario with seven nodes.

10.48047/jocaaa.2024.32.01.66

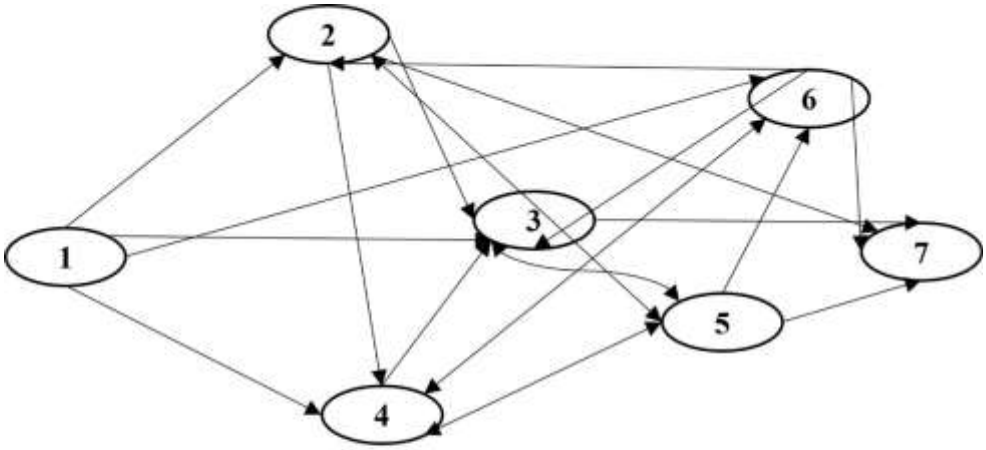


Figure 4. A Scenario with Seven Nodes

Apply the proposed hybrid GWO-GA algorithm with the required modifications to construct the optimal path of EEGGHA. In the given scenario, node 1 is the origin, and node 7 is the BS. The corresponding network graph is shown in Figure 5.

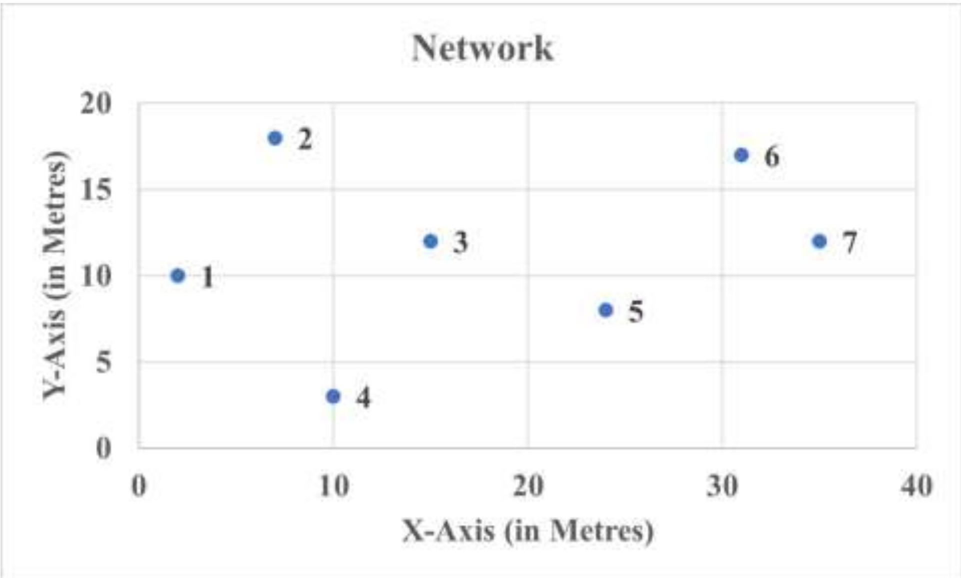


Figure 5. Network Graph for the Given Scenario

In the proposed technique, an individual chromosome represents each path, Parent 1 = {1→2→4→3→6→5→7}, Parent 2 = {1→4→2→3→5→6→7}, Child 3 = {1→4→2→3→6→5→7}, Child 4 = {1→2→4→3→5→6→7}. In a two-dimensional vector space, the Euclidean distance formula is used between two nodes. For Parent 1, it is calculated as d(1→2→4→3→6→5→7) = 74.89m. Similarly, the distance for other paths is also calculated as follows, d(1→4→2→3→5→6→7) = 63.58m, d(1→4→2→3→6→5→7) = 75.79m, d(1→2→4→3→5→6→7) = 62.68m. In the case of multi-hops using Equations (1) and (2), assuming L = 4000 bits and L_{agg} =100 bits, for Parent-1 (1→2→4→3→6→5→7), consider hop 1→2, and d(1, 2) = 9.43m, the EC is,

$$E_{TX}(1, 2) = E_{TX}(4000, 9.43) = 4000x(50x10^{-9}) + (4000x10x10^{-12}) \text{ x } (9.43)^2 = 203.557 \ \mu J$$

10.48047/jocaaa.2024.32.01.66

Node 2 receiving from node 1, $E_{RX}(2) = E_{RX}(4000) = 4000 \times (50\times10^{-9}) = 200\ \mu J$

Hop Energy (HE) for 1→2, the EC is,

$HE = E_{TX}(1, 2) + E_{RX}(2) = 203.557\ \mu J + 200\ \mu J = 403.557\ \mu J$

The EC and HE are given in the Table 1.

Table 1. EC and HE for Parent 1

Path	Hop	Distance (m)	L (bits)	E_{TX} (µJ)	E_{RX} (µJ)	Hop Energy (µJ)
Parent 1	1→2	9.43	4000	203.557	200	403.557
Parent 1	2→ 4	15.30	100	5.234	5.0	10.234
Parent 1	4→3	10.30	100	5.106	5.0	10.106
Parent 1	3→6	16.76	100	5.281	5.0	10.281
Parent 1	6→5	11.40	100	5.130	5.0	10.130
Parent 1	5→7	11.70	100	5.137	5.0	10.137

Similarly, the EC and HE for other paths 1→4→2→3→5→6→7, 1→4→2→3→6→5→7, 1→2→4→3→5→6→7 is calculated. The EC per node for Parent 1 is given in Table 6.

Table 2. EC Per Node for Parent 1

Path	Node	Type	Node Energy Consumed (µJ)
Parent 1	1	Source	203.557
Parent 1	2	CH / Relay	205.234
Parent 1	3	CH / Relay	10.281
Parent 1	4	CH / Relay	10.106
Parent 1	5	CH / Relay	10.137
Parent 1	6	CH / Relay	10.130
Parent 1	7	BS	5.0

Similarly, the EC per node for other paths is also calculated. Table 3 summarizes all the paths.

Table 3. Paths Summary

Chromosome(s)	Path(s)	Total Distance (m)	Total Energy Consumed (µJ)
Parent 1	1→2→4→3→6→5→7	74.89	454.4449
Parent 2	1→4→2→3→5→6→7	63.58	455.1219
Child 3	1→4→2→3→6→5→7	75.79	455.4017
Child 4	1→2→4→3→5→6→7	62.68	454.1651

10.48047/jocaaa.2024.32.01.66

Table 3 shows that Child 4 (454.17 uJ) is now the most energy-efficient path, closely followed by Parent 1 (454.44 uJ). Parent 2 and Child 3 have slightly higher EC (~455 uJ). The path 1→2→4→3→5→6→7 (Child 4) emerges as the energy-efficient path among the four multi-hop options, having the lowest EC, whose cumulative distance is 62.68m. In the case of a single hop, that is, direct-to-BS (from 1→7, d(1, 7) = 33.0606m), the EC is calculated as HE = 443.7199 μJ. This proposed work utilizes the CC2420 sensors, which enable RSSI measurement by accessing the relevant internal registers. An empirical correction value, RSSI_OFFSET, is specified as -45 dBm in the CC2420 datasheet. The CC2420 determines the RSSI of a node based on its distance and an RSSI value given in decibels (dBm). Values over -50 dBm indicate an excellent signal, while readings below -100 dBm indicate an utterly unusable signal. The CC2420 estimated RSSI values and the estimated PDR are mentioned in Table 4.

Table 4. CC2420 RSSI value

Distance	Estimated RSSI Value (dBm)	Estimated PDR (%)
2m	-52.47	1.0
4m	-53.35	1.0
6m	-58.15	1.0
9m	-63.17	0.9
12m	-63.7	0.9
15m	-70.27	0.9
20m	-76.34	0.8
25m	-82.89	0.8

The PDR is calculated using Equation (29) for the path 1→2→4→3→6→5→7 (Parent 1) in the given scenario, as in Table 5.

Table 5. PDR for Parent 1

Path	Hop	Distance (m)	Estimated RSSI (dBm)	Hop PDR (%)
Parent 1	1→2	9.43	-63.246	0.9
Parent 1	2→ 4	15.30	-70.634	0.9
Parent 1	4→3	10.30	-63.4	0.9
Parent 1	3→6	16.76	-72.407	0.9
Parent 1	6→5	11.40	-63.594	0.9
Parent 1	5→7	11.70	-63.647	0.9

10.48047/jocaaa.2024.32.01.66

Similarly, the PDR for other paths 1→4→2→3→5→6→7, 1→4→2→3→6→5→7, 1→2→4→3→5→6→7 is calculated and given in Table 6.

Table 6. PDR of the Paths

Chromosome(s)	Path(s)	Hop PDR (%)	Cumulative PDR (%)
Parent 1	1→2→4→3→6→5→7	0.9 + 0.9 + 0.9 + 0.9 + 0.9 + 0.9 = 5.4	(5.4 / 6) * 100 = 90
Parent 2	1→4→2→3→5→6→7	0.9 + 0.9 + 0.9 + 0.9 + 0.9 + 1.0 = 5.5	(5.5 / 6) * 100 = 91.7
Child 3	1→4→2→3→6→5→7	0.9 + 0.9 + 0.9 + 0.9 + 0.9 + 0.9 = 5.4	(5.4 / 6) * 100 = 90
Child 4	1→2→4→3→5→6→7	0.9 + 0.9 + 0.9 + 0.9 + 0.9 + 1.0 = 5.5	(5.5 / 6) * 100 = 91.7

In the case of a single hop, direct-to-BS (from 1→7, d(1, 7) = 33.0606m), the estimated PDR is 94%. The fitness function for the paths 1→2→4→3→6→5→7, 1→4→2→3→5→6→7, 1→4→2→3→6→5→7, 1→2→4→3→5→6→7, is calculated using Equations (34), (36), (37), and (38) with REs in the range [80 J, 90 J] and with $[\alpha_1, \alpha_2, \alpha_3] = [0.4, 0.3, 0.3]$, which is summarized in Table 7.

Table 7. Fitness Function of EEGGHA for Selection of Optimal Path

Path(s)	f1' = Total Energy Consumed (µJ)	f2' = Cumulative PDR (%)	f3' = Cumulative RE (J)	Fitness function (F)
1→2→4→3→6→5→7	454.4449	90	623	395.68
1→4→2→3→5→6→7	455.1219	91.7	623	396.46 [Fallback path]
1→4→2→3→6→5→7	455.4017	90	623	396.06
1→2→4→3→5→6→7	454.1651	91.7	623	396.08 [Optimal path]

Since the EC, PDR, and RE are collectively paramount, the path 1→2→4→3→5→6→7 (Child 4) appears to be the most favorable and optimal among the multi-hop options. The fallback path is 1→4→2→3→5→6→7 (Parent 2). Figure 6 shows the energy-efficient shortest optimal path selected by EEGGHA for the given sample scenario in Figure 4.

10.48047/jocaaa.2024.32.01.66

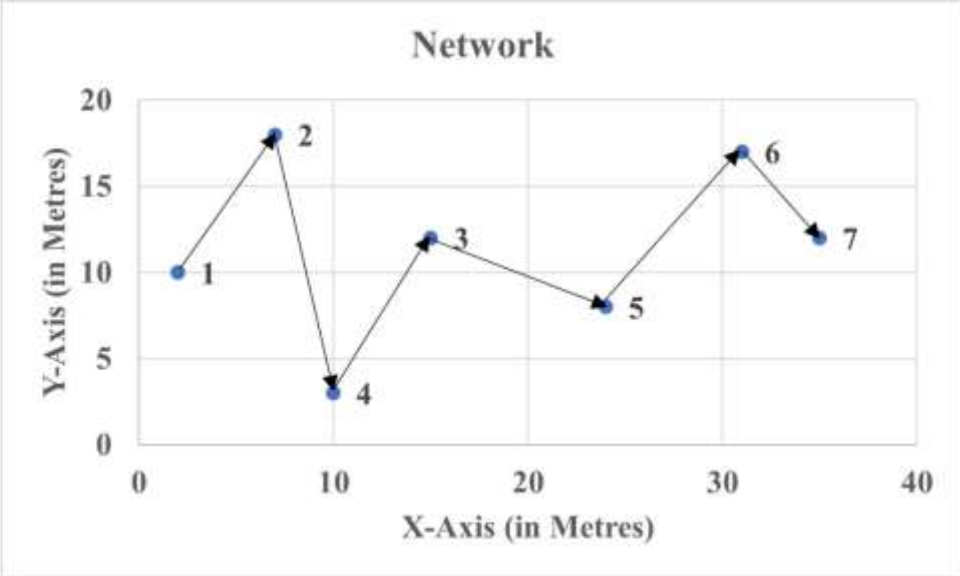


Figure 6. Optimal Path Discovered by the Proposed EEGGHA

4. Simulation Results

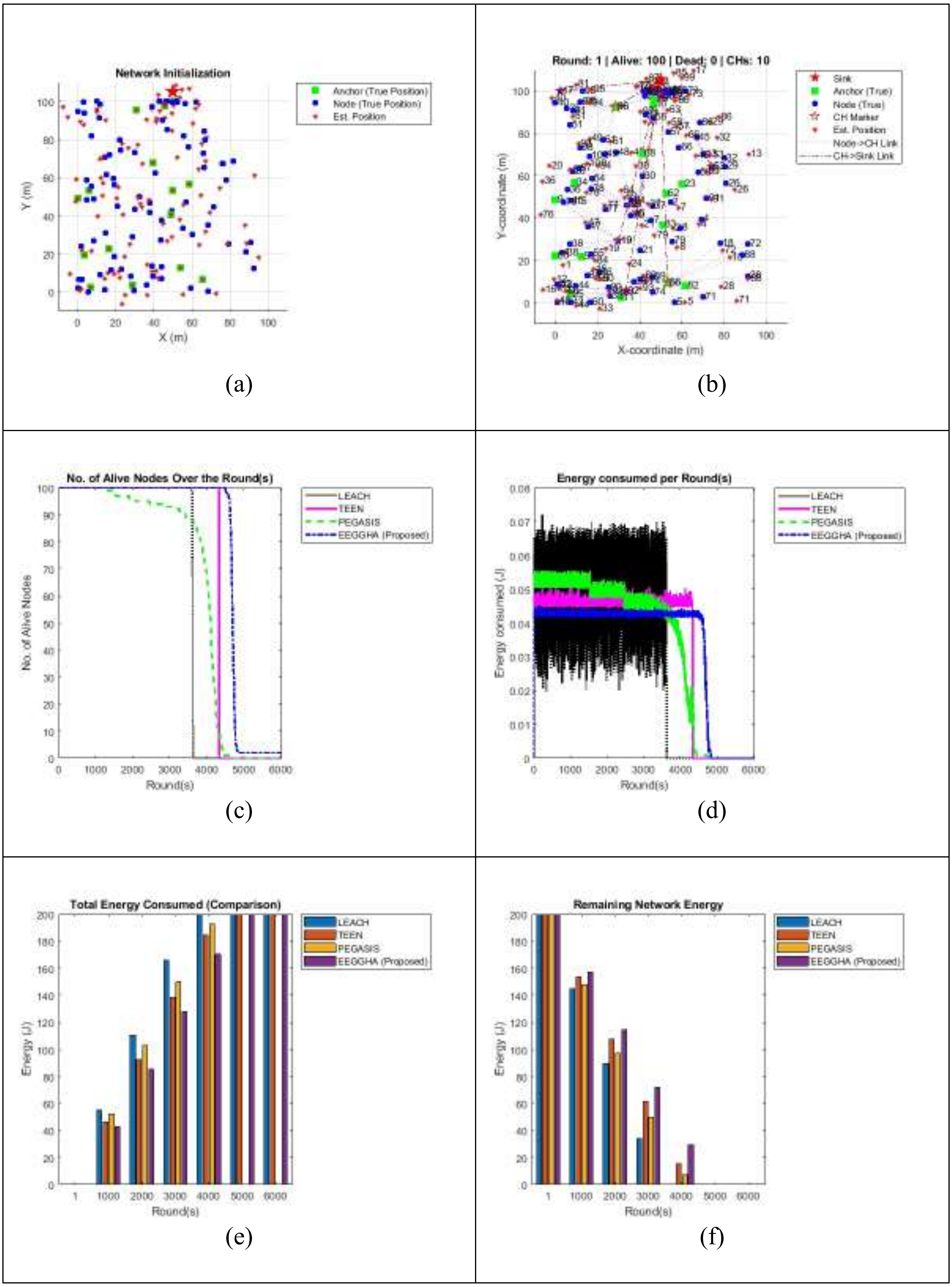
This section summarizes the outcomes achieved with the proposed EEGGHA technique. The proposed method aims to identify effective strategies for reducing energy consumption. The advancement calculation is based on three performance metrics: RE, EC, PDR, and network lifetime. Table 8 displays the simulation specifications for the proposed technique.

Table 8. Simulation Specifications

Parameter(s)	Value
Nodes	100
Size	500 x 500 mts
MAC Layer	IEEE 802.11
Channel Type	Wireless PHY
Traffic Source	CBR
Antenna	Omni antenna
Bandwidth	48 Mbps
Propagation Model	Two – Ray Ground
Packet Size	4000 bits
Initial Energy	2 Joules
Σ_{fs} (d^2 power loss)	10 pJ / bit / m^4
Σ_{mp} (d^4 power loss)	0.0013 pJ / bit / m^2
ETX_{elec} , ERX_{elec}	50 nJ / bit
Population Size	30
Maximum Generations	20-50

A stationary BS is positioned in the upper-middle corner of the network. Only specific nodes serve as anchor nodes and possess a GPS. The remaining nodes are standard ones. Simulations evaluated the performance of the proposed method, EEGGHA, against that of conventional algorithms over 6000 rounds. The simulation results for parameters such as network status, active nodes, EC, RE, PDR, and energy consumed per round are illustrated in Figure 7.

10.48047/jocaaa.2024.32.01.66

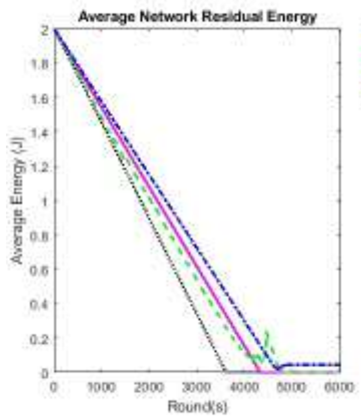


(a) (b)

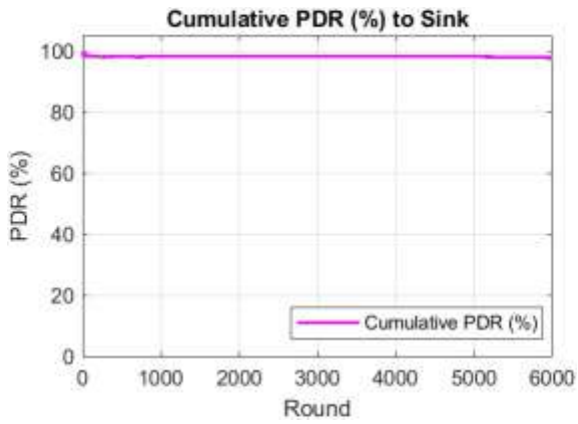
(c) (d)

(e) (f)

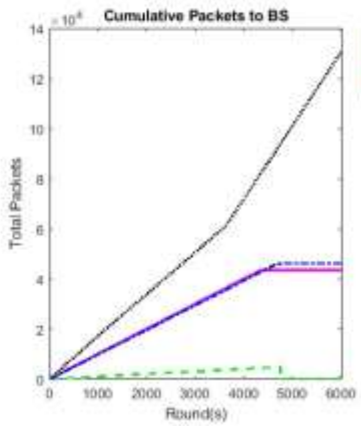
10.48047/jocaaa.2024.32.01.66



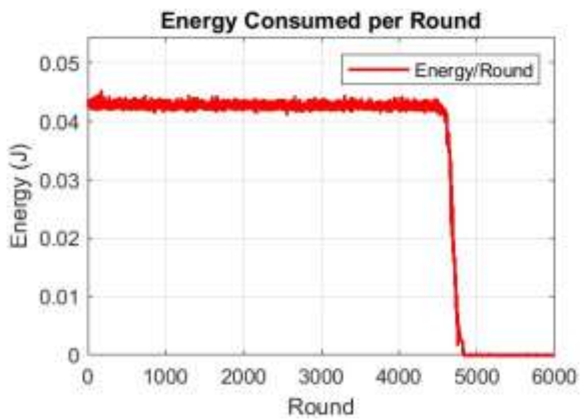
(g)



(h)



(i)



(j)

Figure 7. Comparison of Performance Metrics: (a) Network Initialization, (b) Round 1 Status, (c) No. of Alive Nodes, (d) Energy Consumed Per Round, (e) Total Energy Consumed, (f) Residual Energy, (g) Average Residual Energy, (h) Cumulative PDR of EEGGHA, (i) Cumulative Packets Transmitted to BS, (j) Energy Consumption of EEGGHA

Table 9 compares the outcomes of the First Node Dies (FND), Half Nodes Die (HND), And All Node Dies (AND), and total energy dissipation for the algorithms LEACH, Threshold sensitive Energy Efficient sensor Network protocol (TEEN), Power-Efficient Gathering in Sensor Information System (PEGASIS), and EEGGHA.

10.48047/jocaaa.2024.32.01.66

Table 9. Evaluation of FND, HND, and AND

Algorithm (s)	FND (Rounds)	HND (Rounds)	AND (Rounds)	Total Energy Consumed (%)
LEACH	3572	3615	3629	100
TEEN	4322	4332	4337	100
PEGASIS	1162	4098	4741	100
EEGGHA (Proposed)	4500	4695	>7000	94.74

From Table 9, in the proposed EEGGHA, FND occurs in round 4500, while LEACH, TEEN, and PEGASIS complete 3572, 4322, and 1162 rounds, respectively. The proposed technique surpasses LEACH, TEEN, and PEGASIS by 928, 178, and 3338 rounds. The entire network fails at rounds 3629, 4337, and 4741, respectively. However, the proposed EEGGHA extends its lifespan beyond 7000 rounds. Thus, the proposed EEGGHA is superior to the standard algorithms in terms of FND, HND, AND, and energy consumption.

4.1. Residual Energy

Figure 8 presents the RE comparison for 50, 100, 500, 1000, 2500, and 5000 nodes. The network RE of EEGGHA is the highest compared to other standard algorithms. The average RE of LEACH is 129.74 J, but after about 5000 rounds, the energy is completely drained. So is the case for OP [5] and OERWCA [11]. EEGGHA achieved a 9.26% average RE gain over LEACH. The RE in OP was entirely depleted after around 2500 rounds. EEGGHA achieved a 45.80% average RE gain over OP. EEGGHA improved RE by 31.76% over OERWCA.

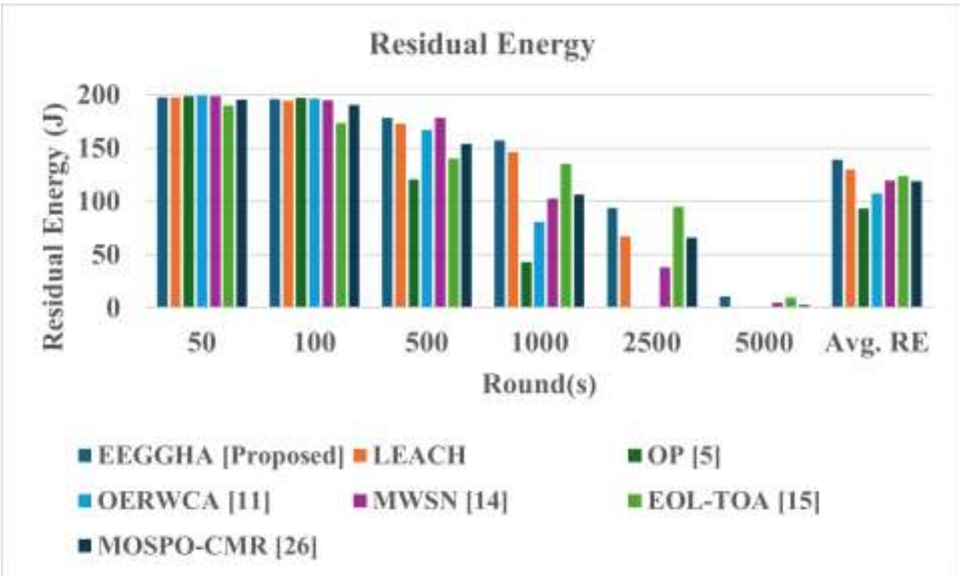


Figure 8. RE Assessment

10.48047/jocaaa.2024.32.01.66

EEGGHA achieved an increased RE of 19.40% compared to MWSN [14]. EEGGHA has boosted RE by 15.02% over EOL-TOA [15]. Additionally, EEGGHA enhanced RE by 19.89% compared to MOSPO-CMR [26]. The results indicate that by the end of 5000 rounds, RE is extended in EEGGHA by 5.26%, resulting in longer battery life and a more prolonged network.

4.2. Network Energy Consumption

Data transmission and processing in sensing nodes also contribute to energy consumption. It is energy-efficient in that it minimizes energy usage through efficient choice of CH and path selection. Additionally, by optimizing its behavior in response to the network's state, it can efficiently distribute the workload among the nodes, thereby avoiding the rapid depletion of energy in some of them. The measure analyzed is the computational cost in terms of energy absorption, as depicted in Figure 9.

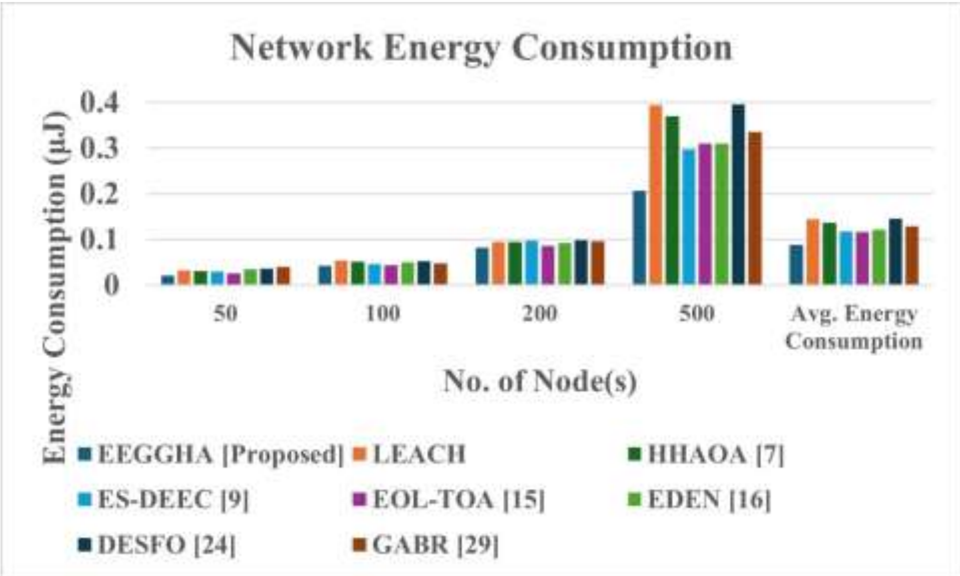


Figure 9. Network EC Assessment

The proposed EEGGHA requires less energy, i.e., 0.0416 µJ per round, than other methods by diagnosing the paths and nodes to select the best possible adaptive CHs, data aggregation, and the optimal path.

5. Conclusion

The IoT is a relatively new field of industrial research that has become increasingly prevalent in people's daily lives. Therefore, the energy consumption of such devices must be modest, as these IoT nodes are designed to be powered by batteries in an always-on state and are typically intended for deployment in remote areas without human intervention. This paper proposed and investigated the hybrid EEGGHA technique to minimize EC for each node in the IoT. EEGGHA is designed to reach the destination node using the smallest amount of energy possible. Reducing EC is crucial for extending the network's longevity. The proposed EEGGHA is evaluated over a range of 1 to 6000 rounds. RE, EC, PDR, and the network's

10.48047/jocaaa.2024.32.01.66

lifetime are analyzed to assess energy efficiency. To demonstrate the effectiveness of this work, it is compared to standard algorithms.

EEGGHA's simulated results outperform schemes such as LEACH, TEEN, PEGASIS, HHAOA, ES-DEEC, OERWCA, EOL-TOA, EDEN, DESFO, MOSPO-CMR, and GABR. The simulation findings indicate that the proposed EEGGHA surpasses existing protocols in every aspect, including an increase in average RE of up to 5.26% and a decrease in average EC of up to 12.4%. Furthermore, the PDR of the proposed technique is 98.25%, and its network lifetime extends to 55 minutes with 500 nodes. In the future, optimal paths based on hybrid optimization and adaptive transmission control could be utilized to achieve better EC outcomes. The proposed technique may be evaluated with a broader range of specification parameters and a more adaptable node count range.

References

1. Mohammed Mohammed, Zaynab Saeed Hameed, Israa Ali Al Al-Neami, Sergey Drominko, and Erina Kovachiskaya. Reduce Energy Consumption and Increase Lifetime via Genetic Algorithm over Wireless Communication Networks. Journal of Intelligent Systems and Internet of Things [Internet]. 2025;14(2):36–43. Available from: http://dx.doi.org/10.54216/jisiot.140204

2. Optimized Resource Allocation for IoT Networks Using Genetic Particle Swarm Optimization and Enhanced K-Nearest Neighbor Algorithms. Tehnicki vjesnik - Technical Gazette [Internet]. 2025 Apr 15;32(2). Available from: http://dx.doi.org/10.17559/tv-20240602001731

3. Turan İH, Yildiz D, Demirci S, Sayit M. Analyzing the Impact of Transmission Strategies on Localization Performance in Wireless Sensor Networks. IEEE Access [Internet]. 2025;13:37673–37689. Available from: http://dx.doi.org/10.1109/access.2025.3545263

4. Chen N, Wen R. Energy Efficient Tree-Based Routing Algorithm for Wireless Sensor Networks. IEEE Access [Internet]. 2025;13:20149–20159. Available from: http://dx.doi.org/10.1109/access.2025.3535229

5. Vishwas HN, Ramesh TK. Recent Trends in Localization, Routing, and Security for Wireless Sensor Networks. IEEE Access [Internet]. 2025;13:55290–55312. Available from: http://dx.doi.org/10.1109/access.2025.3555280

6. Ahmad S, Akhtar N, Ahmed A, Iftikhar S, Bawazeer S, Abdullah S. An Ensemble Formal Approach to Improve Energy Efficiency and Data Aggregation in Smart Agriculture. IEEE Access [Internet]. 2025;13:65316–65333. Available from: http://dx.doi.org/10.1109/access.2025.3558551

7. Tadigotla S, K Murthy J. Enhancing Coverage and Connectivity with Hybrid Harris Hawk and Arithmetic Optimization in Clustering and Routing. 2025 3rd International

10.48047/jocaaa.2024.32.01.66

Conference on Integrated Circuits and Communication Systems (ICICACS) [Internet]. 2025 Feb 21;1–6. Available from: http://dx.doi.org/10.1109/icicacs65178.2025.10968994

8. M S, Kumar S. A Comprehensive Survey on Coverage and Routing Optimization of Wireless Sensor Networks. 2025 International Conference on Multi-Agent Systems for Collaborative Intelligence (ICMSCI) [Internet]. 2025 Jan 20;315–319. Available from: http://dx.doi.org/10.1109/icmsci62561.2025.10893956

9. Anuj Kumar. Improved Swarm based Distributed Energy- Efficient Clustering Protocol for IoT Network using Hybrid Optimization Method. Journal of Information Systems Engineering and Management [Internet]. 2025 Mar 7;10(17s):358–377. Available from: http://dx.doi.org/10.52783/jisem.v10i17s.2742

10. Joon RK, R A, Selvan S, Latha Mageshwari PS, Gayathri Priya S, Malathi K. Unleashing WSN Potential: Bowerbird Optimized Energy-Conscious Multipath Clustering with Causal Dilated Cosine for Enhanced Load Balancing. 2025 4th International Conference on Sentiment Analysis and Deep Learning (ICSADL) [Internet]. 2025 Feb 18;550–556. Available from: http://dx.doi.org/10.1109/icsadl65848.2025.10933076

11. Lv C, Long G. Energy-efficient cluster head selection in Internet of Things networks using an optimized evaporation rate water-cycle algorithm. Journal of Engineering and Applied Science [Internet]. 2025 Mar 5;72(1). Available from: http://dx.doi.org/10.1186/s44147-025-00603-1

12. Abujassar RS. An Innovative Algorithm for Multipath Routing and Energy Efficiency in IoT Across Varied Network Topology Densities. International Journal of Networked and Distributed Computing [Internet]. 2025 Feb 17;13(1). Available from: http://dx.doi.org/10.1007/s44227-024-00041-0

13. Ali Z. Enhancing the Energy Efficiency of Wireless Sensor Networks in IoT. International Journal of Advanced Engineering, Management and Science [Internet]. 2025;11(1):036–60. Available from: http://dx.doi.org/10.22161/ijaems.111.5

14. Mahmoudi Y, Zioui N, Belbachir H. An improved quantum-inspired particle swarm optimisation approach to reduce energy consumption in IoT networks. International Journal of Cognitive Computing in Engineering [Internet]. 2025 Dec;6:313–322. Available from: http://dx.doi.org/10.1016/j.ijcce.2025.01.010

15. Elite-Opposition based Learning Strategy with Tuna Optimization Algorithm for Energy Efficient Clustering and Routing in IoT-WSN. International Journal of Intelligent Engineering and Systems [Internet]. 2025 May 31;18(4):658–670. Available from: http://dx.doi.org/10.22266/ijies2025.0531.43

16. Javadzadeh, Negar & Taghizadeh, Hossein & Sedighi, Mohammap Parsa & Safaei, Bardia & Henkel, Jörg. (2025). EDEN: Energy-aware Dynamic Genetic and Neural Network-based Path Predictive Routing and Clustering for Mobile SD-IoT Networks.

10.48047/jocaaa.2024.32.01.66

17. Aravind K, M PKR. Optimized Fuzzy Logic Based Energy-Efficient Geographical Data Routing in Internet of Things. IEEE Access [Internet]. 2024;12:18913–18930. Available from: http://dx.doi.org/10.1109/access.2024.3354174

18. Paul B, Assi C, Kaddoum G, Palit R, Islam S. An Energy-Efficient Cluster Formation Based on Optimal Node Distribution in Full Capacity Multi-Hop LoRa Networks. IEEE Open Journal of the Communications Society [Internet]. 2024;5:779–794. Available from: http://dx.doi.org/10.1109/ojcoms.2024.3350511

19. Wang Y, Yang Y. A Novel Secure and Energy-efficient Routing Method for the Agricultural Internet of Things Using Whale Optimization Algorithm. Journal of Cyber Security and Mobility [Internet]. 2024 Jun 14;725–750. Available from: http://dx.doi.org/10.13052/jcsm2245-1439.1347

20. Kumar P, Pandey S. Optimizing Sensor Node Placement in Wireless Sensor Networks Using Hybrid PSO-GWO Technique. 2024 IEEE 1st International Conference on Advances in Signal Processing, Power, Communication, and Computing (ASPCC) [Internet]. 2024 Dec 19;85–89. Available from: http://dx.doi.org/10.1109/aspcc62191.2024.10881562

21. Inchara G. P. Energy-Efficient Clustering Routing Protocol using Quad-Tree Divide and Conquer with Dynamic Multihop LEACH for Enhanced IoT Network Lifetime (EECR-IoT). Journal of Electrical Systems [Internet]. 2024 Nov 16;20(11s):1166–1181. Available from: http://dx.doi.org/10.52783/jes.7398

22. Data Aggregation Scheme Using Differential Evolution with Sailfish Optimization for Clustering and Routing in IoT. International Journal of Intelligent Engineering and Systems [Internet]. 2024 Oct 31;17(5):1026–1037. Available from: http://dx.doi.org/10.22266/ijies2024.1031.77

23. Sophia Reena G, Nithya S. Optimized Energy Efficient- Hierarchical Clustering Based Routing (OEE-HCR) For Wireless Sensor Network (WSN). EAI Endorsed Transactions on Energy Web [Internet]. 2024 Jul 3;11. Available from: http://dx.doi.org/10.4108/ew.6504

24. H. El-Sayed H, M. Abd-Elgaber E, Zanaty EA, S. Bakheet S. A Modified LEACH Protocol Using Multi-Hop Mechanism and Neural Networks for IoT Applications. Sohag Journal of Sciences [Internet]. 2024 Sep 1;9(3):274–285. Available from: http://dx.doi.org/10.21608/sjsci.2024.227091.1107

25. Pund IV, Mishra N, Auti NA. IoT-Based Sensor Networks: Evaluating Various Clustering Methods for Energy Efficiency in Wireless Sensor Networks (WSNs). 2024 Global Conference on Communications and Information Technologies (GCCIT) [Internet]. 2024 Oct 25;1–4. Available from: http://dx.doi.org/10.1109/gccit63234.2024.10862032

26. Silva JAL, Costa W, Islam KMM, Deters JK, Bergsma E, Rocha HRO, et al. Improving the Power Consumption of Thread Mesh Networks Through Genetic Algorithm Optimization. IEEE Sensors Letters [Internet]. 2024 Dec;8(12):1–4. Available from: http://dx.doi.org/10.1109/lsens.2024.3488652

10.48047/jocaaa.2024.32.01.66

27. MC S, Saraswathi D, Deepalakshmi R, Jemila SJ, Sathishkumar A. Optimizing Energy-Efficient Routing in Wireless Sensor Networks via Genetic Algorithm for Enhanced Performance. 2024 International Conference on Cybernation and Computation (CYBERCOM) [Internet]. 2024 Nov 15;626–31. Available from: http://dx.doi.org/10.1109/cybercom63683.2024.10803170

28. Al-Atawi AA. Extending the Energy Efficiency of Nodes in an Internet of Things (IoT) System via Robust Clustering Techniques. International Journal of Computer Networks and Applications [Internet]. 2023 Dec 30;10(6):889. Available from: http://dx.doi.org/10.22247/ijcna/2023/223685

29. Kalimuthu VK, Srinivasan B. Multi-objective Sand Piper Optimization Based Clustering with Multihop Routing Technique for IoT Assisted WSN. Brazilian Archives of Biology and Technology [Internet]. 2023;66. Available from: http://dx.doi.org/10.1590/1678-4324-2023220866

30. Chniguir A, Jemaa ZB. Energy-Efficient Improved Optimal K-Means: Dynamic Cluster Head Selection based on Delaying the First Node Death in MWSN-IoT. International journal of Computer Networks & Communications [Internet]. 2023 Sep 28;15(5):37–53. Available from: http://dx.doi.org/10.5121/ijcnc.2023.15503