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An Optimal-Aware Energy Efficient Framework for Energy-Constrained Networks in the Internet of Things

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Abstract

The Internet of Things (IoT) refers to a rapidly expanding network of interconnected devices designed to provide intelligent and context-aware services across various industries, including smart cities, agriculture, healthcare, and industrial automation. This paper studies the creation of an energy-efficient routing framework in the context of the IoT that takes Quality of Service (QoS) parameters into account since existing protocols fail to consider important QoS metrics like Residual Energy (RE), Packet Delivery Ratio (PDR), End-to-End Delay (E2E), latency, throughput, and reliability, amongst others. They aim to improve communication reliability and extend the network lifetime in dynamic IoT scenarios. The proposed technique and framework integrate a QoS-accommodating behaviour in energy-efficient routing, following a multi-criteria decision mechanism based on RE, trust level, Hop Count (HC), node load, and delay. The path selection approach is based on the clustering protocol Threshold Distributed Energy-Efficient Clustering (TDEEC). Still, it incorporates improved performance using metaheuristic algorithms, specifically the hybrid Grey Wolf Optimization and Ant Colony Optimization (GWO-ACO). Challenges, such as the dynamic selection of the Cluster Heads (CHs), adaptively choosing the secure routing path to improve the network for specific QoS requirements relevant to the application, are also addressed. A large number of simulations tests the performance of the proposed technique. The QoS-aware routing model yields noticeable improvements in various performance metrics. It can achieve a PDR of 98.73%, energy savings of 10.81%, and a 10.92% longer network lifetime compared to conventional routing methods. Additionally, it performs well even under variable network conditions, offering improved latency, throughput, reliability, and RE. This paper proposes a new, scalable, and secure routing approach for IoT networks that leverages QoS awareness, energy-efficient clustering, and intelligent path selection through hybrid metaheuristic algorithms. In contrast to conventional methods, this solution can adapt to changes in the network state in a way that ensures the QoS required is still guaranteed, making it a relevant solution for time-sensitive, large-scale IoT applications.

Keywords

Quality of Service, cluster heads, grey wolf optimization, ant colony optimization, security, fairness.

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1. Introduction

The IoT refers to the transformation of the role of physical objects in the digital domain, which involves everyday objects embedded with electronics, software, and network connectivity, such as sensors or appliances [1]. Such incorporation of new technology provides optimal and controllable environmental conditions for a continuous and dependable agricultural output, as well as the means to monitor and automate essential factors centrally. This new system supports better decision-making and space management and is designed to eliminate wastefulness and increase productivity [2]. Another good opportunity for IoT and Wireless Sensor Network (WSN) integration is related to energy efficiency. By utilizing dynamic clustering techniques, it is possible to manage the distribution of energy among the network's nodes, thereby enhancing the network's lifetime. However, a limitation to the development of IoT so far has been poor network reliability due to limited battery life [3]. New communication paradigms can help address such issues, thereby improving energy efficiency, throughput, and adapting to different QoS requirements without requiring a vast amount of computation [4]. The necessity of QoS in the field of IoT arises as follows,

1. Resource-constrained devices, such as IoT nodes, are characterized by limited power and bandwidth.
2. The QoS requirements for service listings between critical and non-critical tasks differ significantly.
3. QoS routing must be flexible to support dynamic topologies, which are often affected by node mobility and node failures.
4. Consequently, the unreliable nature of wireless links necessitates a mechanism for assessing path quality.
5. Communicative paths are secure and trusted because of trust metrics.

In the IoT domain, significant efforts have been devoted to designing clustering and routing techniques to maximize energy efficiency. The motivation behind this research is the need for efficient algorithms that enhance network performance without increasing Energy Consumption (EC). Some of the energy-efficient policies are also explicitly mentioned in Table 1, as they may indicate why the latter would be beneficial for prolonging network lifetime and minimizing latency. However, although useful, these approaches have other drawbacks, as they tend to be computationally expensive, present slow convergence rates, and require a good compromise between energy constraints and heuristic approaches.

Table 1. Evaluation of Various Energy-Efficient Frameworks

Sl. No.	Authors	Year	Methodologies	Goals	Strengths	Limitations
5	Prashanth Kumar et al.	2025	Energy-aware routing with duty cycling and data aggregation	Enhance network longevity and energy efficiency	Significant energy saving, improves data transmission	Does not address dynamic topologies
6	Sheela V, Rathiga P	2025	API-MPSO with SSAD and Round Robin	Optimized clustering and multipath routing to	Balances load, improves lifetime, and energy use	Computationally complex, scalability issues

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			multipath routing	address sink energy holes		
7	Seethamraju S M et al.	2025	PS-COA, RC-FFO, and HPNN-NAI MAC design	Improve MAC efficiency via adaptive clustering and neural control	Extends lifespan and reduces latency	Algorithm overhead may affect smaller networks
8	Amjad Rehman et al.	2025	OLSTM-DVHop	Improve DV-Hop localization with LSTM-based error correction	Superior accuracy and reduced localization error	Higher computation for LSTM training
9	Kumaran S et al.	2023	Adaptive ML-based decision support	Enable flexible environmental monitoring	Handles diverse sensors and dynamic adaptation	Implementation complexity, generic design
10	Preeti Nehra, Sonali Goyal	2023	Wolf Optimization for mobility-aware routing	Optimize node mobility and routing	Improves PDR and reduces delay	Assumes accurate mobility models
11	Yunping Gong et al.	2023	Multi-Objective High Performance Clustering Framework (MHCF)	Optimize energy efficiency and high QoS in industrial IoT	Prolongs sensor lifespan, enhances data reliability	A complex sensor network setup may not scale well in highly dynamic environments
12	Prathap C et al.	2024	GADA-LEACH, Cuckoo search optimizer	Real-time node localization for enhanced positioning	Improves localization accuracy; adequate for static networks	High energy consumption, limited suitability
13	Malarkodi K et al.	2025	Multi-Standard Selection Function (MSSF), Linear Integer Programming Method (LIPM)	Optimize energy efficiency and secure data relay in smart agriculture	Prolongs sensor lifespan, enhances data reliability, and supports sustainable farming	A complex sensor network setup may not scale well in highly dynamic environments
14	Ashish Bapurao Manwatkar et al.	2025	Cross-layer clustering with ACO-based secure routing	Secure and energy-efficient routing for precision agriculture	Improved QoS, energy optimization, and threat mitigation	Framework complexity may need tuning for different agricultural settings
15	Gopal Kumar Gupta et al.	2024	A hybrid framework using PSO and hybrid PSO	Optimize energy efficiency and improve residual energy	Prolongs sensor lifespan, enhances dynamic clustering	High time complexity, and less suitable for real-time networks
16	Khujamatov H et al.	2024	Chaotic Genetic Algorithm and Grey Wolf Optimization (CGA-GWO)	Increase WSN energy efficiency via hybrid CH selection and routing	High residual energy cluster head selection, optimal multi-hop routing	High time complexity

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Nevertheless, areas for improvement include the complexity inherent in the subject of dynamic CH selection, network security, and scalability, as well as the ease of implementation in various challenging IoT scenarios to support reliable and energy-sustainable IoT operations.

1.1. Research Gaps

The specific algorithms highlight critical processes, the character of networks, and some of the impediments to the optimal utilization of global energy resources. But serious concerns regarding fundamental aspects are relevant to significant questions around critical performance metrics. These are:

1. Clustering algorithms lack dynamic adaptability.
2. The lack of attention to the delay-sensitive QoS.
3. Limited support for mobile node scenarios.
4. Learning-based trust and security mechanisms are not used to their full productivity potential.
5. Trade-off between robustness in routing and energy.
6. Absence of an integrated hybrid security, energy, and QoS.
7. Delayed CH selection and routing decisions.
8. Data redundancy and loss of aggregation are not taken into consideration.
9. Non-predictive optimization in reactive protocols.

The main findings are summarized as follows:

1. A new prototype of the cluster-based routing for the IoT, based on the hybrid TDEEC and GWO-ACO algorithm.
2. It also represents one of the fundamental problems that must be addressed in the IoT, namely the tradeoff between EC and guaranteed data delivery.
3. It makes use of the GWO's discovery for clustering and ACO's discovery for routing, and it integrates both GWO and ACO in a way that the energy efficiency and network lifetime outperform the capabilities never seen before.
4. The most essential feature is the hybrid approach, which combines two phases and an adaptive optimization approach. In contrast to the former, this method has certain advantages and avoids some of the aforementioned problems.
5. Energy efficiency, Lifetime of the network, and PDR performance using the new combined scheme also perform significantly better than the standard schemes.

2. Proposed Framework

An architecture is a high-level structural design that defines the components, layers, and communication flow in a system. It answers what the parts are and how they are connected. A framework is a set of tools, libraries, and protocols that provide a concrete implementation of the architecture. It explains the mechanisms for development and execution, as well as the steps for building it. The proposed framework, Path Quality-Aware Adaptive Energy-Governed Intelligent System (PAEGIS), is presented in Figure 1.

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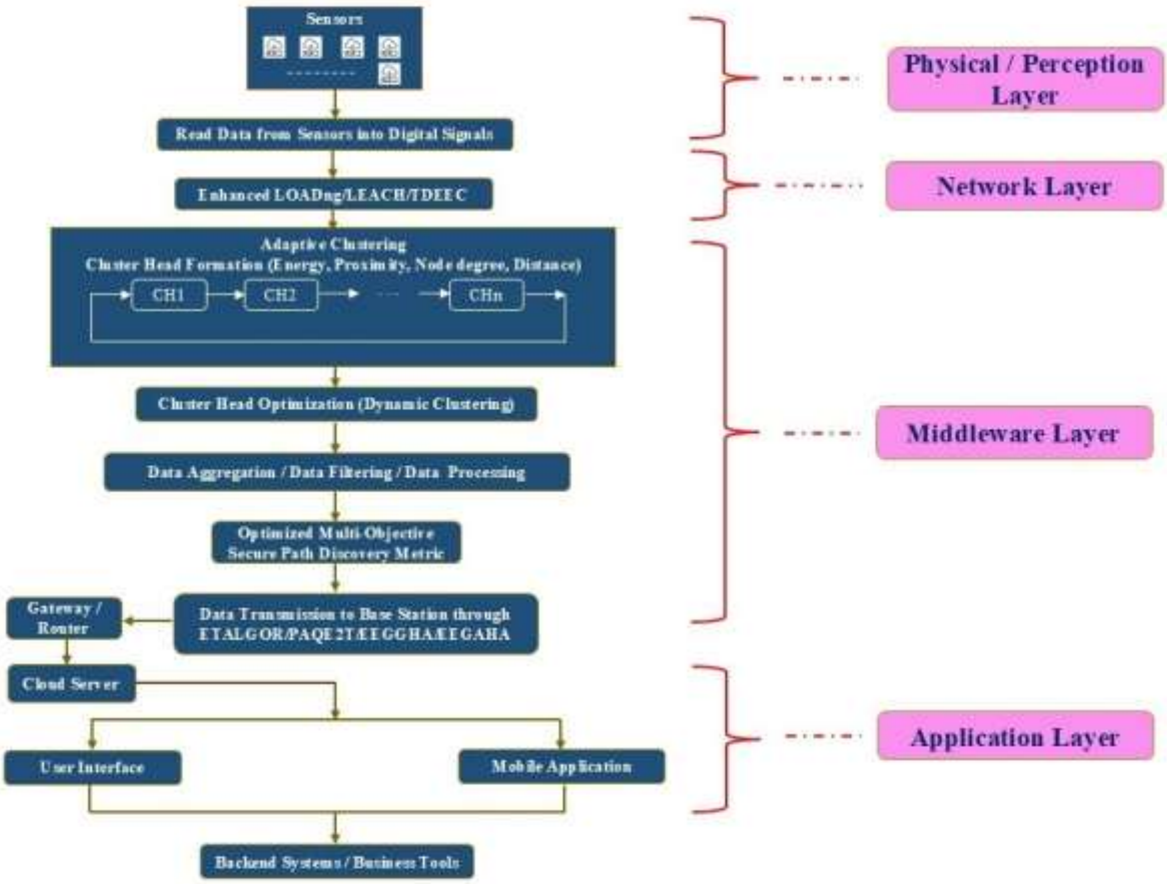

Figure 1. The Proposed Framework, PAEGIS

The network consists of N heterogeneous sensor nodes that interact with one another to sense their environment cooperatively. IoT nodes are uniquely identified and randomly deployed. Nodes have different energy levels, including standard, advanced, super, and hyper nodes, as well as varying memory capacities and processing power.

2.1. Network Model

For the network model, assumptions have been adopted as follows:

- Sensor Nodes (SN) are heterogeneous and have variable resources.
- The SNs are uniformly dispersed.
- SNs have the same coverage area.
- Some nodes are designated as advanced, super, and hyper nodes.
- The mobility of SNs would be before the round’s beginning, moving at a certain velocity, and going to a random area.
- The nodes interconnect with the CH either in single-hop or multi-hop communication.
- According to the Time Division Multiple Access (TDMA) time slot, CHs exchange data with the Base Station (BS).
- The BS is static in the center of the network.

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

2.2. Energy Model

Designing mechanisms for energy conservation becomes, therefore, a crucial issue in the design of IoT networks, given that they typically rely on sensor nodes with batteries of limited capacity. When considering these batteries in various use cases, beyond recharging or replacing them, it becomes clear that optimizing energy expenditure is necessary. Importantly, the expenditure of energy to transport data is enormous; the cost of one bit of data energetically is equivalent to that of many executed instructions. In this sense, the energy budget encompasses the requirements of the network's components, including the radio, CPU, and sensors, to prolong the network's lifetime. By relating the communication cost to packet size, a significant issue is that the energy required for data to travel from SNs to the BS is highly dependent on the data.

Equations (1) and (2) specify the first-order radio model for transmitting and receiving energy with a $l - bit$ packet over a distance of d [17, 18] using Adaptive Transmission-power Control (ATC).

$$E_{TX}\left(l, L_j, d\right) = l * E_{elec} + l * \epsilon_{amp}\ (L_j) * d^{\alpha} \tag{1}$$

$$E_{RX}(l) = l * E_{elec} \tag{2}$$

$$d(i,j) = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{3}$$

Where E_{TX}, E_{RX} → Data transmission and reception energy, E_{elec} → Energy spent powering the transmitter and receiver on and off, ϵ_{amp} → ϵ_{fs} or ϵ_{mp} based on distance, L_j → Power level of a node, and α → path loss exponent (2 or 4). The threshold distance is represented by 'd_o' and is expressed as in Equation (4).

$$d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} = 87m \tag{4}$$

ATC describes methods that change transmission power and other parameters, such as data rate, based on real-time varying network conditions, and should be implemented in the design of IoT. This could be key to achieving the highest energy efficiency, improving link quality, and resulting in robust communication in constantly changing environments. The adaptive transmission control logic is given in Equation (5).

$$E_{adaptiveTX}(L, d, Type) = \omega_{Type} * E_{TX}(L, d) \tag{5}$$

Where L → Load of a node, Type → Regular, advanced, or super nodes, and ω_{Type} is given in Table 2.

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Table 2. Node Adaptive Transmission Energy

Node Type	Weight (ω_{Type})
Regular node	1
Advanced node	1 / (1+α)
Super node	1 / (1+β)
Hyper node	1 / (1+γ)

The primary purpose of data aggregation is to conserve energy and reduce data redundancy. This directly leads to a longer operational lifetime for individual nodes and the network as a whole, along with reduced network traffic and congestion. The CH typically conducts the data aggregation phase during the steady-state phase, after receiving data packets from its member nodes. Equation (6) and (7) gives the EC for non-CH nodes.

$$E_{nonCH} = (E_{RX} * L_{ctrl}) + (E_{TX} * L_{data}) + \left(\epsilon_{fs} * L_{data} * d_{toCH}^2\right) \tag{6}$$

$$E_{CH} = (N * E_{RX} * L_{data}) + \left(E_{TX} * L_{agg}\right) + \left(\epsilon_{mp} * L_{agg} * d_{toBS}^4\right) \tag{7}$$

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.

3. Mathematical Model of the Proposed Technique

The cohesive implementation of modified energy-efficient TDEEC, GWO, and ACO hybrid (EEGAHA) is a tool that can provide better support for localization and routing in heterogeneous IoT networks. GWO takes into account aspects such as RE and distance to BS, for node localization as well as for the CH selection, and it employs a hierarchical structure of Alpha, Beta, and Delta wolves for guiding the optimization process and providing the necessary environment for an effective deployment of CHs. Finally, the use of ACO to improve routing, secure energy-efficient routing paths, and fulfill performance indexes such as link quality and EC is performed. ACO benefits from its routing strategy, which uses pheromone updating and stochastic pathfinding to maintain a capacity for adaptation. This hybrid GWO-ACO achieves scalability, good performance, and security in the IoT system, which is particularly beneficial in situations where centralized algorithms fail to function effectively. It also offers a good packet delivery ratio and enables long-term network operation.

3.1. Node Mobility

Dynamicity represents movements in the network structure; for instance, sensor nodes, relay nodes, or data sinks may move around the deployment area. Adaptive routing techniques are necessary to achieve sink mobility, thereby balancing EC around the sink. Focusing only on the former:

1. Mobile Sensors: Nodes that can be transported.
2. Mobile Relays: Nodes that move to assist in data forwarding, optimizing the paths of communication.
3. Mobile Sinks: A moving base station that gathers data from sensor nodes.

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The benefits of mobility in IoT systems are primarily related to the ability to provide greater network coverage, balance energy expenditure, increase channel capacity, and enable new applications in the mobile environment, such as environmental sampling and dynamic surveillance. The position of node i at time t is given in Equations (8) and (9).

$$P_i(t) = \left(x_i(t), y_i(t)\right) \tag{8}$$

and

$$P_i(t + \Delta t) = P_i(t) + \left(v_i(t) * \cos\theta_i\,(t) * \Delta t, v_i(t) * \sin\theta_i\,(t) * \Delta t\right) \tag{9}$$

Where $v_i(t)$ is the velocity of the node, $\theta_i(t)$ is the direction of the node.

3.2. Localization with GWO

Consider (x_u, y_u) as the calculated coordinates of node u. Let A is denoted as the collection of anchor nodes, each with specified locations (x_j, y_j). RSSI at distance d is modeled as,

$$d_{uj} = P_t - PL(d_0) - 10 * \mu * \log_{10}\left(\frac{d}{d_0}\right) + X_\sigma \tag{10.1}$$

Where P_t → Transmission power, $PL(d_0)$ → Pathloss reference, μ → Pathloss exponent, and X_σ → Gaussian variable. The fitness of the node's estimated location is calculated as,

$$fitness_{loc}(x_u, y_u) = \sum_{j \in A} w_j \left(\sqrt{\left(x_u - x_j\right)^2 + \left(y_u - y_j\right)^2} - d_{uj}\right)^2 + \lambda \tag{10.2}$$

Where w_j are weights, d_{uj} is the RSSI distance, λ is the penalty for inconsistent node positions. The GWO algorithm minimizes this fitness function.

3.3. Cluster Establishment

Each cluster can only be part of a single cluster, and cluster creation is the key to clustering protocols since it structures the network into clusters. To ensure energy efficiency, the design process of CHs must be conducted in multiple stages, considering the constraints of the IoT, to reduce EC and maximize residual energy. Specific nodes are chosen as CHs according to some parameters such as energy, degree, delay, or location, and clusters are formed around these CHs based on proximity. During the setup phase, the network must be initialized by specifying the number of nodes, denoted N, categorized into four types of heterogeneity: regular, advanced, super, and hyper nodes. After that, more nodes are grouped into predetermined clusters, in which the CHs are chosen based on the proximity to the BS. The adaptive cluster formation fitness score (F_{CH}), which considers the metrics of RE, distance, delay, and security while favoring the better nodes, is given in Equation (11).

$$F_{CH_i} = \alpha_1 * \left(\frac{E_{max}}{E_{RE_i}}\right) + \alpha_2 * \left(\frac{d(i, BS) + d(i, NN_{avg})}{2 * d_{max}}\right) + \alpha_3 * \left(\frac{D_i}{D_{max}}\right) + \alpha_4 * \left(\frac{S_{max}}{S_i}\right) \tag{11}$$

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Where E_{RE} → Residual energy of a node, E_{max} → Maximum RE, d(i,BS) → Distance from node i to BS, $d(i,NN_{avg})$ → Avg. distance from node i to neighboring nodes, Di → Delay of a node, S_i → Security level of a node, α_1 to α_4 → Weights assigned to each metric based on network state. All terms are inversely proportional, i.e., higher energy, closer distance, lower delay, and better security reduce the cost.

A node becomes a CH if $F_{CH} > F_{Threshold,}$ which is defined as a dynamic value. The optimal selection percentage of each node type as a CH is defined in Equation (12), where the goal is to leverage powerful nodes as CHs.

$$CH_{opt} = \sqrt{\frac{N}{2\pi}} * \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} * \frac{M}{d_{toBS}^2} * [(1 - m - b - c) + m(1 + \alpha) + b(1 + \beta) + c(1 + \gamma)](12)$$

Where M → Network area, m → Fraction of advanced nodes, b → Fraction of super nodes, α → Advanced nodes energy factor, β → Super nodes energy factor, and γ → Hyper nodes energy factor.

The rules for optimal CH selection in the proposed EEGAHA are defined using three constraints as follows:

i. For all the eligible nodes, compute the CH score (F_{CH}) using Equation (11).
ii. Rank the scores derived in step (i).
iii. Select the optimal number of CHs using Equation (12) having the lowest scores for F_{CH}.

Once a node is nominated as the CH, the non-CH nodes join the nearest CH as Cluster Members (CMs) based on the composite cost metric given in Equation (13.1).

$$Cost_{CM}^{ij} = \lambda_1 * \left(\frac{d_{ij}}{d_{max}}\right) + \lambda_2 * \left(\frac{1}{E_j(t)}\right) + \lambda_3 * \left(\frac{1}{S_j(t)}\right) \quad (13.1)$$

Where d_{ij} → Distance from node i to CH j, $E_j(t)$ → RE of CH j, $S_j(t)$ → Security level of CH j, and λ_1 to λ_3 → Weights for distance, RE, security.

A node joins the nearest CH with the minimum cost, as determined by Equation (13.2).

$$CM_i \to CH_j, if\ CH_j = \arg\min_{j \epsilon CHs} \left(Cost_{CM}^{ij}\right) \quad (13.2)$$

To avert the overloading of a weaker CH, the condition is given in Equation (13.3). This condition ensures that super or advanced CHs support a larger number of members.

$$n_j^{max} = \varphi * \frac{E_j(t)}{E(0)} \quad (13.3)$$

Where n_j^{max} → Maximum number of members for CH j, φ → Avg. cluster size, Ej(t) → RE of CH j, and E(0) → Regular, advanced, or super node energy. A CH accepts a node as member if $n_j < n_j^{max}$.

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Each CH should prevent premature energy depletion and manage an optimal number of cluster members. The optimized number of cluster members is given in Equation (13.4).

$$CH_{Members_{opt}} = \frac{N}{CH_{opt}} \tag{13.4}$$

Where N → Number of nodes, CH_{opt} → Optimal number of CH. This ensures an equal distribution of nodes across clusters, optimizing load and energy usage; however, individual cluster sizes can vary significantly based on CH capability.

The steady-state phase is the operational phase after the initial setup. During this period, sensor nodes actively monitor the environment, including data transmission and energy management. The inter-cluster communication is defined in Equation (14.1), and intra-cluster communication is defined in Equation (14.2).

$$E_{nonCH} = E_{sense} + E_{TX}\left(k, L_j, d\left(i, CH_j\right)\right) + E_{RX}(k) \tag{14.1}$$

$$E_{CH} = E_{CHDA} + E_{TX}\left(k', L_j, d(CH_i, BS)\right) \tag{14.2}$$

Where E_{TX}, E_{RX} → Transmission and reception energy, E_{CHDA} → Energy for data aggregation by CH, d → Distance to CH or to BS, and L_j →Power level of a node. This accounts for energy used in intra-cluster and inter-cluster communications, promoting efficient energy usage through data aggregation.

Re-clustering refers to a dynamic process driven by the need to adapt to changing network conditions and maintain operational efficiency. Periodically reorganizing the clusters and rotating CH roles prevents energy drain on specific nodes. More capable nodes might serve as CHs for longer durations or less frequently to conserve their energy for critical tasks, or more regularly if they are dedicated CHs. CH rotation is designed to distribute the energy load associated with the CH role among multiple sensor nodes over the network's lifetime. The initial energy, $E0_{IE}$, of different types of heterogeneous nodes is defined in Equation (15).

$$E_{IE}(0) = \begin{cases} E0_{IE}, for\ Regular\ nodes \\ E0_{IE}(1+\alpha), for\ Advanced\ nodes \\ E0_{IE}(1+\beta), for\ Super\ nodes \end{cases} \tag{15}$$

Where $E0_{IE}$ → Initial energy of normal nodes. The probability of regular, advanced, and super nodes becoming a CH is given in Equation (16). This ensures uniform CH rotation over time, preventing energy drain on specific nodes.

$$P_i(t) = \begin{cases} P_{optimal} * \dfrac{E_{IE_i}(t)}{\overline{E_{IE}(t)}}, if\ E_{IE_i}(t) > CH_{Threshold} \\ 0, Otherwise \end{cases} \tag{16}$$

Where a threshold energy, $CH_{Threshold}$, bounds the probability to avoid low-energy nodes becoming CHs, which is defined as in Equation (17).

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$$CH_{Threshold} = \overline{E_{IE}(t)} * \left(1 + \frac{a}{r}\right) \quad (17)$$

Where $E_{IE}(t)$ → Avg. RE of the network, a → Tuning parameter, r → Current round. The dynamic threshold $T(i)$ considers the probability of each node being a CH, as given in Equation (18).

$$T_i = \begin{cases} \dfrac{P_i(t)}{1 - r + P_i(t) * r * \left\lfloor \dfrac{1}{P_i(t)} \right\rfloor}, if\ i\epsilon G \\ 0, Otherwise \end{cases} \quad (18)$$

Where G → The set of regular, advanced, super nodes not elected as CH in the last $1/Pi(t)$ rounds, and r → Current round. A node is reelected as CH if Random [0, 1] < T(i). This balances the CH election based on real-time energy awareness, achieving energy fairness, and extending the network lifetime.

Even with the limitations of the network, effective data handling and transmission ensure the efficient and reliable delivery of sensed information. At this level, one works with individual data packets and processes them using techniques such as data aggregation to conserve resources. This involves packaging at the source, transmitting data across one or multiple relay nodes, and unpackaging at the destination. Excessive traffic can result in buffer overflows, and therefore, there is a need for congestion control. Additionally, it is more energy-efficient than end-to-end retransmission schemes, as recovery efforts are confined to the area where the packet loss was detected and can be handled at the hop level. Equation (19) defines communication between a single non-CH node with different energy levels and its CH.

$$E_{intraTX}(i) = \alpha_i * \begin{cases} s * E_{elec} + s * \epsilon_{fs} * d_{i,CH}^2, if\ d_{i,CH} < d_0 \\ s * E_{elec} + s * \epsilon_{mp} * d_{i,CH}^4, if\ d_{i,CH} \geq d_0 \end{cases} \quad (19)$$

Where s → Message size, E_{elec} → Electronics circuit energy, d_0 → Threshold distance, and

$$\alpha_i = \begin{cases} 1, if\ Regular\ node \\ \dfrac{1}{1+\alpha}, if\ Advanced\ node \\ \dfrac{1}{1+\beta}, if\ Super\ node \end{cases} \quad (20)$$

For n member nodes in the cluster, define,

$$E_{intraTX} = \sum_{i=1}^{n-1} E_{intraTX}(i) \quad (21)$$

CH receives packets from the nodes, as specified in Equation (22).

$$E_{intraCHRX} = m * s * E_{elec} \quad (22)$$

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Data communication between clusters, typically from CH to relay CH or CH to BS, focuses on minimizing the energy cost of transmissions while ensuring link reliability. Equations (23), (24), and (25) define the inter-cluster communication with data aggregation. For a source CH,

$$E_{interCHTX} = \alpha_{CH} * s * E_{DA} + E_{TX}\big(s, d(CH, RelayCH)\big) \tag{23}$$

For a relay CH,

$$E_{RelayCHTX} = \alpha_{RelayCH} * s * E_{elec} + E_{TX}\big(s, d(RelayCH, BS)\big) \tag{24}$$

For the reception of the relay CH,

$$E_{RelayCHRX} = m * s * E_{elec} \tag{25}$$

Where α → Weight for heterogeneous nodes, E_{DA} → Data aggregation energy, and m → Number of packets. This balances multiple relay characteristics and prioritizes nodes with ample energy to sustain the relay task (receiving and transmitting). For a direct hop from source CH to BS,

$$E_{interTX} = s * E_{DA} + E_{TX}\big(s, d(CH, BS)\big) \tag{26}$$

Where s → Message size, E_{DA} → Data aggregation energy, and E_{TX} → Transmission energy.

3.4. ACO in the Proposed Technique

ACO is an example of a metaheuristic developed based on the foraging capabilities of ants and their ability to find the shortest path through pheromone trails in a complex network. This method can be seen as determining efficient, secure, and reliable data forwarding paths from the SNs to the BS. In ACO, the artificial ants search for solutions based on pheromone level and heuristic information, such as residual energy and link delay. On their way, ants leave pheromones of varying strengths according to the effort invested in their trajectory. As time passes, superior paths are strengthened by an increase in pheromone content, while less successful ones are diminished over time through pheromone evaporation. Consequently, the ACO algorithm will preferably generate superior solutions such as exploring nature of the algorithm and the updating of pheromones' progress.

Define a composite Link Selection Function (LSF) for choosing a link from node i→j, incorporating energy, load, delay, and security given in Equation (27.1).

$$LSF_{ij} = \left(\frac{E_j(t)}{E_{max}}\right)^{\mu} * \left(\frac{1}{L_j(t)+1}\right)^{\rho} * \left(\frac{S_j(t)}{S_{max}}\right)^{\sigma} * \left(\frac{1}{H_{ij}+1}\right)^{\gamma} \tag{27.1}$$

Where E_j → RE of node j, L_j → Load at node j, S_j → Security level of node j, H_{ij} → Hop count.

The load metric $L_j(t)$ for a node j at the receiving end of the hop is defined in Equation (27.2).

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$$L_j(t) = \begin{cases} \omega_1\left(\frac{Q_{current}^{(j)}}{Q_{max}^{(j)}}\right) + \omega_2\left(\frac{CPU_{util}^{(j)}}{CPU_{max}^{(j)}}\right) + \omega_3\left(\frac{E_{RE}^{(j)}}{E_{IE}^{(j)}}\right), if\ node\ j\ is\ non\ CH \\ \omega_1\left(\frac{Q_{current}^{(j)}}{Q_{max}^{(j)}}\right) + \omega_2\left(\frac{CPU_{util}^{(j)}}{CPU_{max}^{(j)}}\right) + \omega_3\left(\frac{E_{RE}^{(j)}}{E_{IE}^{(j)}}\right) + \omega_4\left(\frac{N_{mem}^{(j)}}{N_{max}^{(j)}}\right), if\ node\ j\ is\ CH \end{cases} \quad (27.2)$$

Where Q → Current queue length of node j, CPU → Current CPU utilization of node j, ω_1 to ω_4 → Weights for load components, and N → Number of active members of a CH.

The pheromone update rule for local update during the ants' movement is defined in Equation (28).

$$\tau_{ij}(t) = (1-\rho) * \tau_{ij}(t) + \rho * \tau_0, for\ Local\ update \quad (28)$$

Where ρ → Pheromone evaporation rate, τ_0 → Initial pheromone.

The probability of choosing a link from node i→j is given by,

$$P_{ij}(t) = \frac{\left[\tau_{ij}(t)\right]^{\alpha} * \left[LSF_{ij}\right]^{\beta}}{\sum_{k\epsilon N_i}[\tau_{ik}(t)]^{\alpha} * [LSF_{ik}]^{\beta}} \quad (29)$$

Where N_i → Neighbor set of nodes i, τ_{ij} → Pheromone value of link (i,j), and LHF → Link selection function. A link with high pheromone, high energy, low load, high security, and low delay is more likely to be chosen.

3.5. Optimal Path Selection using ACO

The goal is to identify the optimal path from an origin node to the BS based on a cost metric, often by minimizing the network's total EC and maximizing its lifespan. Each path cost is calculated using the composite fitness function ($Cost_{path}$) presented in Equation (30).

$$Cost_{path}(m) = \sum_{(i,j)\in path}\left(\lambda_1\frac{E_{max}}{E_{ij}(t)} + \lambda_2\frac{L_{ij}(t)}{L_{max}} + \lambda_3\frac{S_{max}}{S_{ij}(t)} + \lambda_4\frac{H_{ij}}{H_{max}} + \lambda_5\frac{D_{ij}}{D_{max}}\right) \quad (30)$$

Where m → Paths in a network, λ_1 to λ_5 → Weights for RE of a path, load of a path, security of a path, hop count, and delay of a node.

The pheromone update rule for global update if a link i→j is in the path $path_m$ found by ant m is defined in Equations (31) and (32).

$$\tau_{ij}(t+1) = (1-\rho) * \tau_{ij}(t) + \sum_m \Delta\tau_{ij}(m), for\ Global\ update \quad (31)$$

$$\Delta\tau_{ij}(m) = \begin{cases} \frac{Q}{Cost_{path}(m)}, if\ ij\ \in path_m\ found\ by\ ant\ m \\ 0, Otherwise \end{cases} \quad (32)$$

Where Q → Pheremone constant, $Cost_{path}$ → Obtained from Equation (30).

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In Equation (30), the security factor (S_{ij}) is derived from the following conditions,

i. Successful decryption/authentication count.
ii. Reputation scores from packet integrity checks.

And given in Equation (33) using the TinySec security protocol.

$$S_{ij}(t) = \sum_{i,j \epsilon path} Security_{ij} \tag{33}$$

Where $Security_{ij}$ → Security level of link i→j is defined by TinySec protocol.

The optimal secure path is selected by the proposed EEGAHA using Equation (34).

$$Fitness(path) = \max_{m \in path} \frac{1}{Cost_{path}(m)} \tag{34}$$

3.6. Energy Consumption of the Proposed Technique, EEGAHA

The EC calculations of the proposed technique at different levels, specifically focusing on a single round, are given. Equations (1) and (2) define the EC of a node for transmission and reception. The EC of a non-CH node is given in Equation (35).

$$E_{nonCH}^{(i)} = E_{sense} + E_{proc} + E_{sleep} + E_{idle} + E_{TX}(l, L, d) + E_{RX}(l) \tag{35}$$

Where i → Node i, E_{sense} → Sensing energy, E_{proc} → Processing energy, E_{idle} → Idle energy, E_{sleep} → Sleep energy, E_{TX} → Transmission energy to CH, and E_{RX} → Reception energy of nodes. The processing energy of a node is given in Equation (36).

$$E_{proc}^{(i)} = m * E_{DA} \tag{36}$$

Where m → Message size, and E_{DA} → Data aggregation energy. The EC of a CH is defined in Equation (37) according to the type: regular, advanced, or super nodes.

$$E_{CH}^{(i)} = \omega * \begin{cases} E_{TX}(k, L, d) + E_{DA}, if\ CH\ is\ source\ node \\ E_{RX}(k) + E_{TX}(k, L, d), if\ CH\ is\ relay\ node \end{cases} \tag{37}$$

Where ω → Weight of the type of node given in Table 1.

The EC of a node in a round is given in Equation (38).

$$E_{consumed}^{(i)}(r) = \begin{cases} E_{nonCH}^{(i)}(r), if\ node\ is\ non\ CH\ in\ round\ r \\ E_{CH}^{(i)}(r), if\ node\ is\ CH\ in\ round\ r \\ E_{idle}^{(i)}(r), if\ node\ is\ idle\ in\ round\ r \end{cases} \tag{38}$$

Where i → Node i, and r → Round. The RE of a node at the end of a round is calculated as in Equation (39).

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$$E_{RE}^{(i)}(r) = E_{RE}^{(i)}(r-1) - E_{consumed}^{(i)}(r) \tag{39}$$

Where r → Round. The overall EC by all nodes in the network for a single round, as well as the total energy consumed across all rounds, is given in Equations (40) and (41).

$$E_{totalConsumptionPerRound}(r) = \sum_{i=1}^{n} E_{consumed}^{(i)}(r) \tag{40}$$

$$E_{totalConsumed} = \sum_{i=1}^{r} E_{totalConsumptionPerRound}(i) \tag{41}$$

Where r → Number of rounds, and n → Quantity of nodes in the network.

The cumulative RE of all the active nodes in the network during round r is defined in Equation (42).

$$E_{Net}(r) = \sum_{i=1}^{N_{active}(r)} E_{RE}^{(i)}(r) \tag{42}$$

Where $N_{active}(r)$ → Nodes active in the network during a round, and E_{RE} → Residual energy of a node. The nodes may be regular, advanced, super, CHs, or intermediate relaying nodes. The average EC of non-CH and CH nodes in a network is given in Equations (43) and (44).

$$\overline{E_{nonCH}} = \frac{1}{N-k} * \sum_{i=1}^{N-k} E_{nonCH}^{(i)} \tag{43}$$

$$\overline{E_{CH}} = \frac{1}{k} * \sum_{i=1}^{k} E_{CH}^{(i)} \tag{44}$$

Where N → Quantity of nodes, k → Number of CHs.

The average RE of nodes in a network is given in Equation (45). This results in monitoring energy distribution and the overall health of the network.

$$\overline{E_{RE}} = \frac{1}{N} * \sum_{i=1}^{N} E_{RE}^{(i)} \tag{45}$$

Where N → Number of nodes.

3.7. Pseudocode of the Proposed Technique

Beneath are detailed instructions for generating an optimized hybrid GWO-ACO solution used in the proposed work, EEGAHA. First, apply the GWO algorithm to find node localization and optimal CH placement.

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Procedure GWO()
Begin
Input: Measured_distances ← d_m[j], Search_range ← {min, max}, N, MaxIterations
Output: X_alpha ← Projected position of the target node

1. X_i, ← {i = 1, …, N}
2. t = 0
3. Fitness f(X_i) ← Calculate for all wolves using Equation (10.2)
4. Find best X_alpha, X_beta, X_delta
5. WHILE t < MaxIterations DO
6. a ← 2 – t *(2 / MaxIterations)
7. FOR each wolf X_i DO
8. FOR each dimension d = 1 to dimension DO // (i.e., dimension = 2 for 2D)
9. Generate A1, A2, A3 ← a and C1, C2, C3 ← a
10. Compute D_alpha, D_beta, D_delta
11. Calculate X1, X2, X3
12. X_i(t+1) ← (X1 + X2 + X3) / 3
13. END FOR
14. Apply boundary check on X_i(t+1)
15. END FOR
16. Evaluate new fitness f(X_i(t+1)) for all wolves using Equation (10.2)
17. IF new Fitness is best THEN
18. Find X_alpha, X_beta, X_delta
19. END IF
20. t ← t + 1
21. END WHILE
22. RETURN X_alpha

End

The ACO algorithm is now used to find the energy-efficient and optimal secure path to reach the BS from the source, which maximizes RE and PDR and minimizes EC.

Procedure ACO()
n: number of nodes
m: number of ants
A []: an array of all the possible paths
S: a set of constraints
MaxIterations: maximum ACO iterations
Begin

1. τ[i][j] ← All edges between nodes i and j
2. η[i][j] ← Path quality
3. Iter ← 0
4. WHILE Iter < MaxIterations DO
5. FOR each ant k = 1 to m DO
6. Initialize the path starting from the source
7. WHILE destination not reached DO
8. Next node ← using Equation (29)
9. END WHILE
10. Population ← Completed path
11. END FOR
12. $Cost_{path}$ ← Calculate fitness using Equation (30)
13. τ[i][j] ← Update using Equation (31)
14. Apply Elitism and preserve the best global path
15. Iter ← Iter + 1
16. END WHILE
17. Fitness(path) ← max {1 / $Cost_{path}$}
18. RETURN $Cost_{path}$

End

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3.8. Mathematical Proof of the Proposed Technique, EEGAHA

Apply the proposed hybrid modified TDEEC-GWO-ACO algorithm to construct the optimal secured path for EEGAHA. In the given scenario, node 1 is the source, and node 7 is the BS. The corresponding network graph is shown in Figure 2.

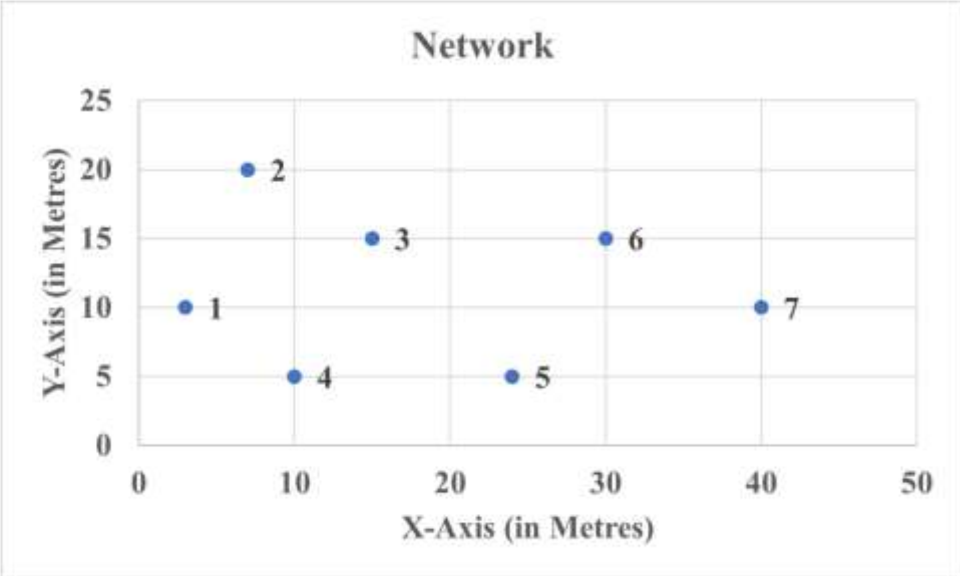

Figure 2. An Example Scenario

In the proposed technique, each path is represented as 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. The distance between two nodes is calculated using the Euclidean distance, which is calculated as follows: d(1→2→4→3→6→5→7) = 80.67m, d(1→4→2→3→5→6→7) = 69.63m, d(1→4→2→3→6→5→7) = 76.76m, and d(1→2→4→3→5→6→7) = 73.54m. The parameter values used in the equations are given in Tables 3 and 4.

Table 3. Assigned Parameters

Parameters	Assigned optimal values
λ_1 (Energy), λ_2 (Load), λ_3 (Hops), λ_4 (Security), λ_5 (Delay)	0.4, 0.15, 0.3, 0.05, 0.1
E_{max} (Energy)	100.0 J
L_{max} (Load), S_{max} (Security), H_{max} (Hops), D_{max} (Delay)	1.0, 10, 6, 5.0 ms
ω_1 (Queue), ω_2 (CPU)	0.5, 0.5

The delay is calculated as given in Equation (46).

$$Delay\ (ms) = Distance\ (m) * 0.1 \tag{46}$$

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Where Distance(m) → Total distance of the path.

Table 4. Node Parameter Values

Node ID	Current Queue (Out of 50)	CPU Utilization (%)	Security Level (1-10)	RE (J)
1	5	10%	9	95
2	15	30%	8	90
3	35	60%	3	85
4	20	25%	7	90
5	10	20%	9	85
6	25	40%	5	85
7	2	5%	10	100

Using Equations (1), (2), (3), (27.1), (27.2), (29), (30), (33), and (34), calculate the EC, ACO path cost, and fitness of the path are given in Table 5.

Table 5. ACO and Fitness Path Evaluation

Path ID	Total Distance (m)	Total Energy Consumption (J)	Relay Nodes	Hop Count	Security Trust Score	Total Delay (ms)	Path Cost (ACO Score)	Fitness
1	80.67	0.001245	2,4,3,6,5	6	1.7057	8.067	1.082	0.9242
2	69.63	0.001234	4,2,3,5,6	6	1.7057	6.963	1.0798	0.9261 [Optimal secure path]
3	76.76	0.001242	4,2,3,6,5	6	1.7057	7.676	1.0812	0.9249
4	73.54	0.001237	2,4,3,5,6	6	1.7057	7.354	1.0806	0.9254 [Fallback path]

Table 5 shows that path 2 is the most energy-efficient secure path, with a fitness of 0.9261, closely followed by path 4, which has a fitness of 0.9254. This proposed work utilizes the CC2420 sensors. Figure 3 illustrates the optimal secure energy-efficient path selected by EEGAHA for the scenario presented in Figure 2.

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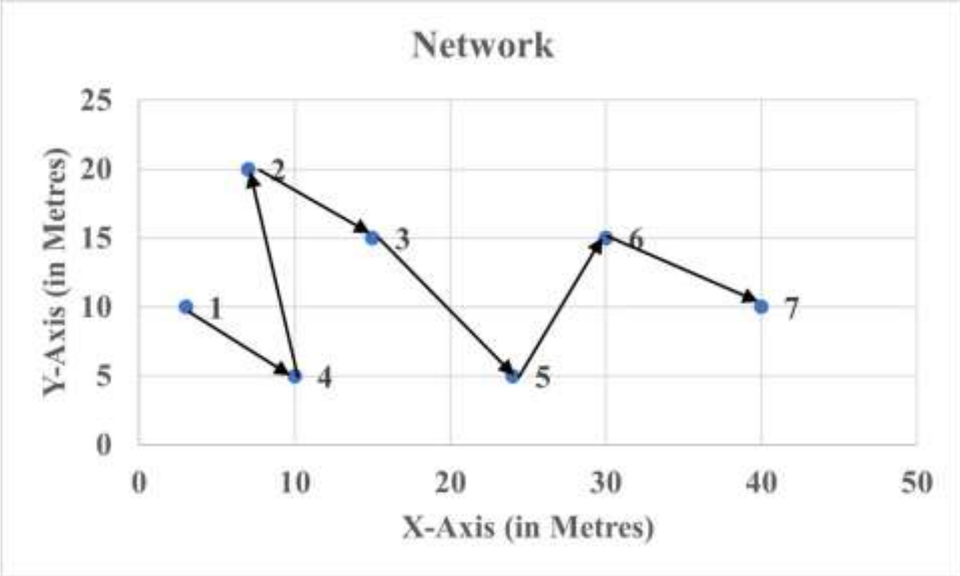

Figure 3. Optimal Secure Path Discovered by the Proposed EEGAHA

4. Simulation Results

This segment summarizes the simulation results obtained for the proposed EEGAHA technique. The proposed method aims to identify effective strategies for reducing EC. Table 6 presents the simulation specification for the proposed technique.

Table 6. Simulation Specifications

Parameter	Value
Number of Nodes	100
Network 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 (19,20)
Σ_{mp} (d^4 power loss)	0.0013 pJ / bit / m^2 (19,20)
ETX_{elec} , ERX_{elec}	50 nJ / bit (19,20)
Maximum Iterations	20-50

4.1. QoS Metrics Estimation

QoS metrics in IoT measure the performance, reliability, and efficiency of data transmission in sensor networks. These metrics are crucial for evaluating and comparing routing or clustering protocols, particularly in energy-constrained and application-specific IoT environments. The formulas for key QoS metrics measured by the proposed EEGAHA are presented below. The EC of each node is given in Equation (47).

$$E_{consumed} = E_{IE} - E_{RE} \tag{47}$$

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The total EC of the network is given in Equation (48).

$$E_{total} = \sum_{i=1}^{N} E_{IE}^{i} - E_{RE}^{i} \tag{48}$$

Where IE → Initial energy and N → Quantity of nodes. The total delay is given in Equation (49).

$$Delay_{E2E} = \frac{1}{N} \sum_{i=1}^{N} \left(T_{received}^{i} - T_{sent}^{i}\right) \tag{49}$$

Where T_{sent} → Time when a packet is sent, and $T_{received}$ → Time when a packet is received. The PDR is measured as in Equation (50).

$$PDR = \frac{Pkts_{received}}{Pkts_{sent}} * 100 \tag{50}$$

Where $Pkts_{sent}$ → Number of packets sent from nodes, and $Pkts_{received}$ → Number of packets successfully received. Throughput is defined as the total data received by a node. during a time interval, which is given in Equation (51).

$$Throughput = \frac{\sum_{i=1}^{N} Pkt\ Size_{i}}{Total\ Time} \tag{51}$$

Where Pkt Size → Size of each packet. Jitter is a parameter that measures the variability in packet delay, as given in Equation (52).

$$Jitter = \frac{1}{N-1} \sum_{i=2}^{N} \left|Delay_{E2E}^{i} - Delay_{E2E}^{i-1}\right| \tag{52}$$

Where $Delay_{E2E}$ → Packet delay. The Fairness Index is defined as the data sent by a node, or CH selection count, as given in Equation (53).

$$FI = \frac{\left(\sum_{i=1}^{N} x_{i}\right)^{2}}{N * \sum_{i=1}^{N} x_{i}^{2}} \tag{53}$$

Where x_i → Data sent by a node or CH selection count, and FI ∈ {0, 1}. Latency is defined as the time for a data packet to travel from a SN to a gateway or an application, as expressed in Equation (54).

$$Latency = \frac{1}{N} \sum_{i=1}^{N} \left(Time_{response}^{i} - Time_{request}^{i}\right) \tag{54}$$

In IoT, low latency is paramount to ensure timely responses in real-time applications. Reliability refers to the probability that a packet will be delivered successfully to its intended

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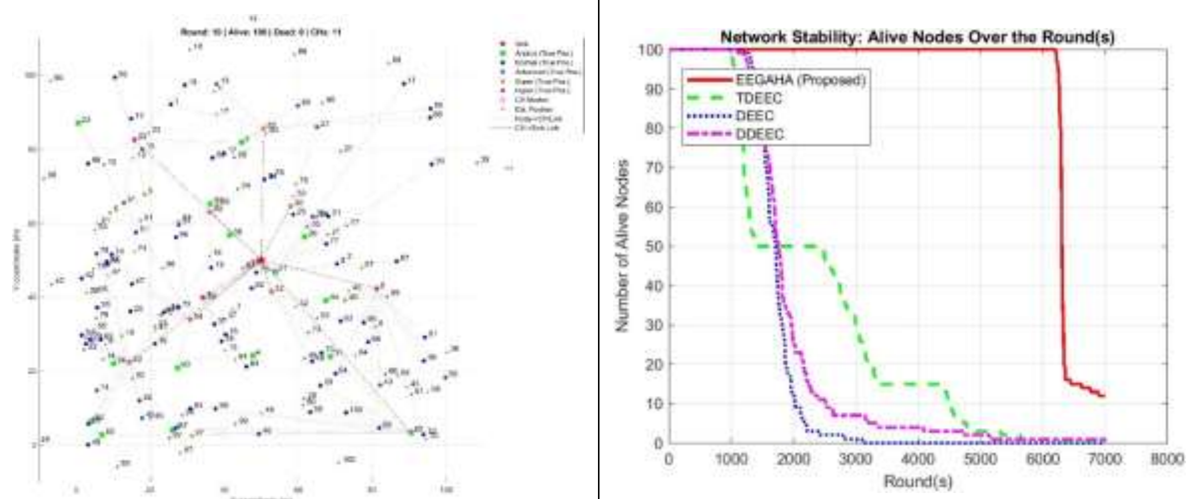
endpoint, which is derived from PDR. The various QoS metrics measured for the proposed EEGAHA are presented in Table 7.

Table 7. Evaluation of QoS Metrics for Proposed EEGAHA

Path ID	Total Distance (m)	Total Energy Consumption (J)	Total Delay (ms)	PDR (%)	Throughput (Kbps)	Jitter (ms)	Fairness Index (FI)	Latency (ms)	Reliability
Path 1	80.67	0.001245	8.067	93.0940	380.798	53.1262	1	836.7269	0.9309
Path 2	69.63	0.001234	6.963	98.7311	441.194	26.3800	1	726.2923	0.9873
Path 3	76.76	0.001242	7.676	94.3616	400.2172	41.8047	1	797.5832	0.9436
Path 4	73.54	0.001237	7.354	97.3890	417.7114	37.7015	1	765.4360	0.9739

From Table 7, it is apparent that path 2 is optimal in terms of distance, EC, delay, PDR, throughput, jitter, latency, and reliability, closely followed by path 4.

The nodes in the network are categorized into four types: standard, advanced, super, and hyper nodes. A stationary BS is in the center of the network. Simulations compared the performance of the proposed technique, EEGAHA, against that of standard algorithms over 7000 rounds. The simulation results for parameters such as network status, alive nodes, EC, residual energy, PDR, and time complexity are presented in Figure 4.



(a) (b)

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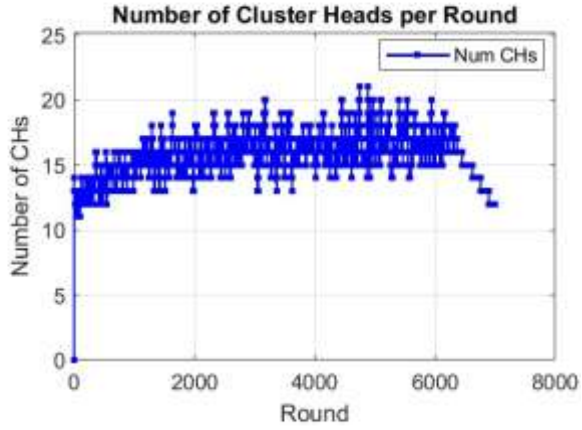

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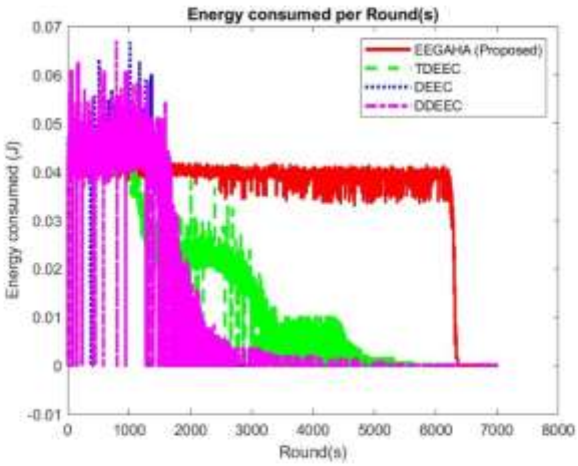
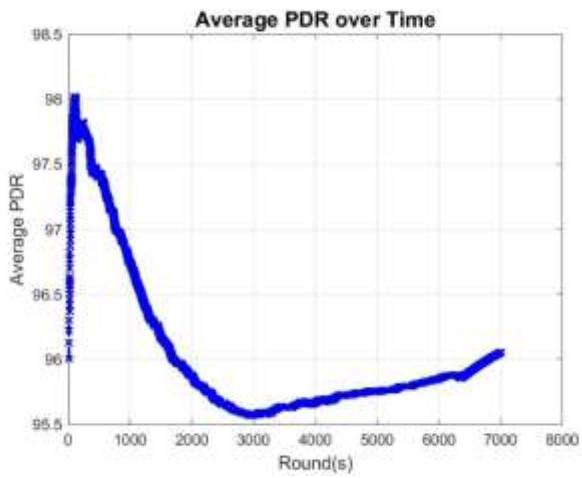
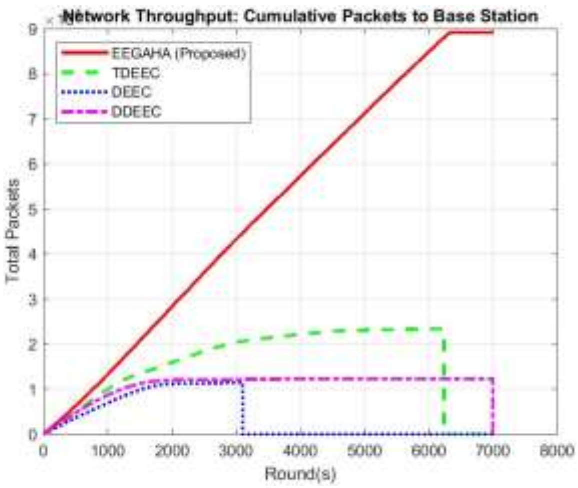


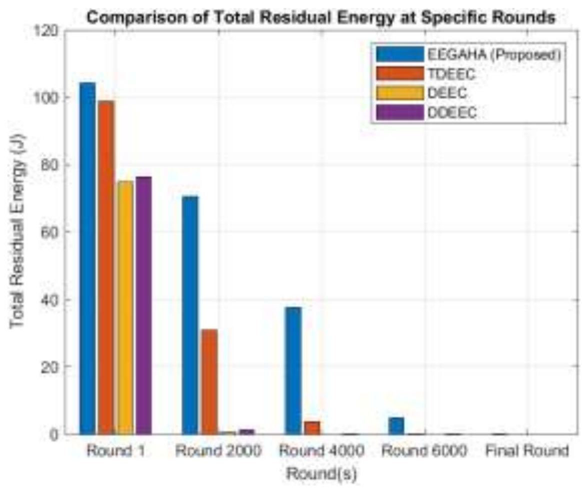
(d)



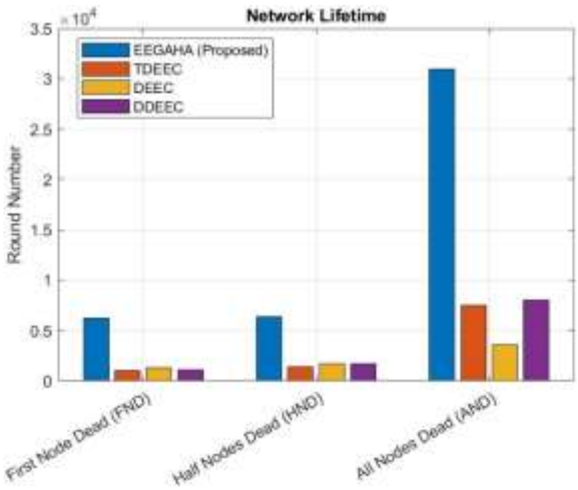
(e)



(f)



(g)



(h)

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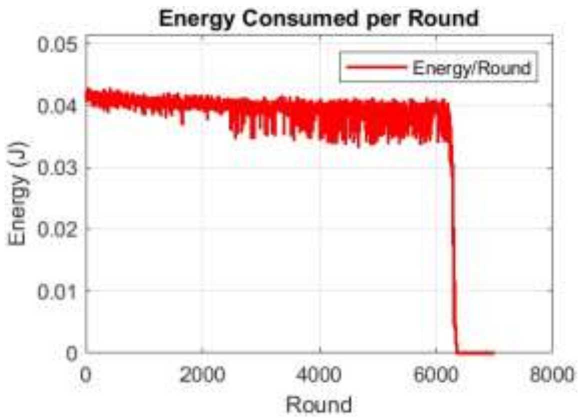
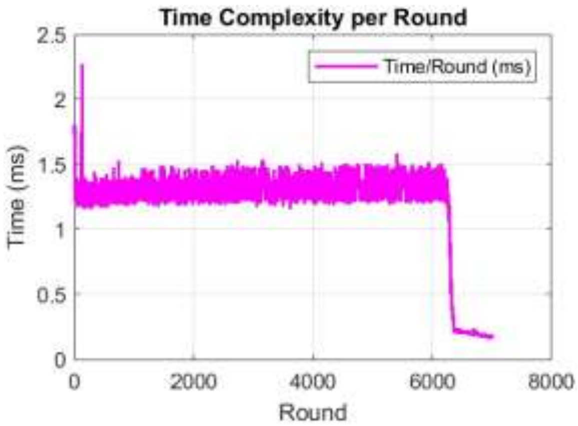


(i)



(j)

Figure 4. Assessment of QoS metrics: (a) Network topology, (b) No. of alive nodes, (c) No. of CHs per round, (d) Energy consumed per round, (e) Avg. PDR over time, (f) Throughput, (g) Total residual energy, (h) Network lifetime, (i) Energy consumed per round, (j) Time complexity of EEGAHA.

From Figure 4, it is concluded that the proposed EEGAHA outperforms standard algorithms such as TDEEC, Distributed Energy-Efficient Clustering (DEEC), and Developed Distributed Energy-Efficient Clustering (DDEEC) in every aspect. Three parameters define the network lifetime,

1. First Node Dies (FND) – The round when first node runs out of energy.
2. Half Nodes Die (HND) – The round when 50% of the nodes in the network are dead.
3. Last Node Dies (LND) – The round when last node runs out of energy.

Table 8 compares the results of the FND, HND, LND, and total energy dissipation for the algorithms TDEEC, DEEC, DDEEC, and EEGAHA.

Table 8. Estimation of Network Lifetime

Algorithm (s)	FND (Rounds)	HND (Rounds)	LND (Rounds)	Total Energy Consumed (%)
TDEEC	1008	1418	6235	96.38
DEEC	1210	1712	3100	100
DDEEC	1112	1754	7000	97.94
EEGAHA (Proposed)	6205	6305	64060	89.19

From Table 8, it is apparent that FND of the proposed EEGAHA occurs in round 6205, whereas TDEEC, DEEC, and DDEEC occur in rounds 1008, 1210, and 1112, respectively.

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The network lifetime for EEGAHA, TDEEC, DEEC, and DDEEC is 64060, 6235, 3100, and 7000, respectively. The lifetime of the proposed EEGAHA is prolonged by 10.92%. The total energy dissipated by the proposed EEGAHA after 7000 rounds is 89.19%. Thus, the proposed EEGAHA is superior to the TDEEC, DEEC, and DDEEC algorithms in terms of FND, HND, LND, and energy dissipation. The proposed EEGAHA is compared with other algorithms in terms of QoS metrics, and the results are presented in Table 9.

Table 9. Evaluation of QoS Metrics

Algorithms	Network Lifetime (Rounds)	Total Energy Consumption (J)	Total Delay (ms)	PDR (%)	Throughput (Kbps)	Fairness Index (FI)
IPIRP [1]	6603	16.88	-	94.30	85.44	-
EEHCT [2]	10157	242.5	-	-	-	-
EARP [5]	13000	30.1	-	73.19	-	-
API-MPSO [6]	18000	8.8	33	80.6	57	0.052
EDA [10]	-	715.25	13	-	4.5	-
GADA-LEACH [12]	3500	390.03	309.34	98.2	79	-
OCLRI-ACO [14]	8100	36	8.2	95.3	-	0.049
ISSA-C [17]	5400	210	10	96.0	1.0	-
EEGAHA (Proposed)	64060	11.09	6.963	98.73	441.194	1.0

From Table 9, after analyzing various QoS metrics, the proposed technique, EEGAHA, outperforms other algorithms, ensuring consistent, energy-efficient, secure, and optimal performance in heterogeneous networks.

5. Conclusion

The focus of this work is the introduction of an energy-efficient hybrid clustering technique, referred to as EEGAHA, within the context of an IoT heterogeneous network. The heterogeneous network environment required to achieve the goals of EEGAHA does not necessitate a specific level of heterogeneity; in general, EEGAHA effectively accomplishes its

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primary objectives of enhancing QoS metrics such as PDR, network lifetime, and stability. It also specifies a technique for creating a cluster of energy-balanced clusters, known as the dynamic clustering technique.

EEGAHA offers the best performance in both network lifetime and network stability among other existing schemes, including TDEEC, DEEC, and DDEEC. Also, not being based on the heterogeneity of the network solution is a very scalable scheme. The approach in this work is to design the proposed EEGAHA and proposed PAEGIS framework so that it minimizes the EC reaching the destination and maximizes the PDR. It is also a priority to sustain the network's life. This EEGAHA is then assessed on a scale of 1 to 7000 rounds. The results demonstrate that the proposed work is comparable to standard algorithms.

EEGAHA performs better in simulations than TDEEC, DEEC, DDEEC, IPIRP, EEHCT, EARP, API-MPSO, EDA, GADA-LEACH, OCLRI-ACO, and ISSA-C. The simulation results reveal that the introduced EEGGHA outperforms the other approaches in all terms, resulting in a 10.81% decrease in EC. The PDR of the proposed method is 98.73%, and the network lifetime is improved by 10.92%. In the future, it would be possible to exploit the energy hole issue and optimal paths based on adaptive transmission power control, for interesting EC outcomes and, possibly, different topologies.

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