

Gray Wolf Optimization Based Clustering Using Network Parameters for WSN Applications

Simran Patkar^{1,*}, Alok Mishra², Aashu Kori³

Abstract

Modern communication systems need to use energy. This is very important for the Internet of things which's a big network of smart devices that talk to each other. The Internet of Things is becoming very popular because it is useful. This paper is about a way to send data in a Wireless Sensor Network. We made a routing protocol that works well in a simulated environment. Our approach is to make the cluster head selection process better. We do this by using a technique that optimizes the process and compresses data at the cluster heads. We also made a system that chooses cluster heads in a specific way. This system uses an optimization strategy to make sure that sensor data is sent efficiently. We have developed an energy-efficient routing strategy to make the sensor networks last longer. Our new protocol uses less energy than traditional methods. This means that the sensor nodes last longer and the network lifetime is extended. The new protocol is better than protocols like LEACH and PEGASIS. It is 60% better when we measure the first node death round. It is also 20% better than the optimized DEEC routing protocol when it comes to energy efficiency. The Internet of Things and Wireless Sensor Networks will work better with our protocol.

Keywords: IoT, WSN, clustering, GWO, data compression, wavelet transform

INTRODUCTION

IoT creates intelligent, automated, and efficient settings across numerous domains to increase human well-being [1]. Its rapid development in environmental monitoring, smart homes, and healthcare services has made it a major driver of the industrial revolution [2–4]. Sensor nodes in distant or hostile areas with limited battery resources are used in Internet of Things (IoT) systems. The demand for energy-efficient IoT solutions is increasing [5–7]. A key component of IoT infrastructure is WSNs, which power such systems' connectivity [8]. Clustering approaches in WSNs increase system performance by increasing energy efficiency and network longevity [9, 10]. When choosing a cluster

head (CH), coverage, node centrality, and residual energy are considered [11]. Communication in sensor nodes uses much more energy than sensing or processing [12]. Nodes far from the static sink use single-hop communication, which consumes a lot of energy [13], whereas nodes near the sink use multi-hop data forwarding, which depletes energy more quickly [14]. Consequently, energy holes are generated [15, 16]. Such solutions may increase the control overhead owing to frequent topology modifications [17].

The suggested approach in this study selects an ideal collection of CHs and compresses data following aggregation at the CHs. The technique uses energy-aware routing to assess network and node metrics to estimate the CH set fitness for optimum selection. A fitness function that integrates

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residual energy and node location enables effective clustering to decrease energy consumption and improve the IoT network performance. It also reduces the Wireless Sensor Network transmission overhead and improves scalability. Gray Wolf Optimization (GWO) is used to find the best CHs, and DEEC routing is used to transmit data. The Adaptively Scanned Wavelet Difference Reduction (ASWDR) compresses the aggregated data at each CH after clustering, reducing energy use and network lifetime. The efficacy of the proposed method was verified through simulation and comparison with standard routing protocols. Section II describes the methodology, Section III presents the simulation-based performance analysis, and Section IV summarizes the study.

METHODOLOGY

This section provides an effective clustering approach and structured routing strategy to decrease the energy consumption of IoT sensor nodes and increase the network lifespan. The goals are data collection and transmission to CHs. The GWO-based Energy-Aware Clustering with ASWDR compression (GWOEACASWDR) improves the network lifespan by increasing the network coverage and efficiency. The procedure involves three stages: The first step involves clustering and CH selection utilizing network characteristics to evaluate the fitness of CH sets, where the GWO meta-heuristic method improves system stability and energy efficiency. The second step compresses the CH data using ASWDR before transmission to the base station to reduce the energy hole problem, energy consumption, communication cost, and energy dissipation. In the third phase, the DEEC protocol is used to efficiently route the sensed data to the base station via CHs or directly to increase the lifetime of the present CH and reduce energy consumption without affecting the surrounding CHs.

Assumptions Considered Under Protocol Simulation

Several assumptions underlie the proposed protocol. IoT sensor nodes are randomly distributed and immobile throughout their lifespan. Recharging is impossible because all nodes are homogeneous and have finite energy. The node transmission of energy depends on the communication distance. The BS is central to the sensing field. The network region ($m \times m$) is split into clusters, each with a single CH selected using the GWO method. We assume single-hop transmission between the sensor nodes and CHs.

Network Model

In this network topology, N static, restricted IoT sensor nodes are randomly distributed in an $m \times m$ sensing region. Each node has a unique ID $[1, 2, \dots, N]$ and uses GPS to locate its position (x_i, y_i) relative to the field center. Initially, the BS sends hello messages with its position. Each sensor node alerts its nearest neighbor with its identifier, geographical coordinates, and initial energy. The GWO algorithm selects the most competent node as the CH and organizes the network into clusters. The BS communicates the sensor roles, CH identification, node locations, residual energy levels, and nearby CH information for each cell in rounds. The setup and steady-state stages comprise each round. The setup step includes CH selection, next-hop determination, and transmission scheduling. In the steady state, the sensor data and residual energy information are sent to the CH, then to the next hop, and finally to the BS. The CH allocates transmission slots among nodes using TDMA to reduce intra-cluster interference. ASWDR-based data compression following data aggregation at each CH reduces energy usage. Locally, each CH aggregates data and sends residual energy information to the BS.

Cluster Fitness Parameters

Analysis of WSNs lifespan and energy consumption variables identifies essential parameters for the optimization technique to improve routing performance. This study evaluated the following parameters.

- Converging function ($F_{converging}$):* The sum of the sensor node-cluster head distances is the intra-cluster distance. A cluster is efficient when most nodes are near the CH.
- Diverging function ($F_{diverging}$):* The total cluster center distance. Clusters that are farther apart perform better, ensuring better separation.

- c. *CH centrality*: This factor shows how near the CH is to the cluster's geometric center, indicating a balanced cluster formation.
- d. *Node degree*: The percentage of cluster nodes to the total number of nodes. A greater number indicates that the cluster covers more networks. The energy required to transmit data is reduced by a shorter distance between the CH and base station.
- e. *CH Residual energy ($E_{Res}(CH)$)*: For sustained and efficient network operation, the selected CHs should have greater residual energy Table 1.

Six network parameters— f_{conv} (f_1), f_{div} (f_2), centrality (f_3), node degree (f_4), DCH-to-BS (f_5), and E_{Res} are used to evaluate the CHs set fitness. Each parameter contributes differently. To optimize performance, some factors must be increased, whereas others must be decreased. For efficient CH selection, the divergence function and residual energy must be larger, whereas the remaining factors have the opposite effect on CH appropriateness for WSN data transmission, as shown in Table 2. The fitness function is proportional to $\{f_{div}, E_{Res}(CH)\}$. Fitness is inversely proportional to $\{f_{conv}, \text{centrality}, \text{Dist}_{CH \text{ to BS}}, \text{Node}_{degree}\}$.

Table 1. Scheme for the evaluation of various fitness parameters.

Number of CHs=Number of clusters= C Number of nodes within a cluster= N_c	
Summation of distances of nodes to CHs = $\sum_{i=1}^{N_c} D_{Si-CH}$	(1)
$F_{converg.} = \sum_{j=1}^C D_{cluster}^j$	(2)
Distance in CHs= $D_{CHi \text{ to } CHj}$;	
$F_{diverg.} = \sum_{i=1}^C \sum_{j=1}^C D_{CHi \text{ to } CHj}$	(3)
Centrality is defined by:	
$\text{Centrality}_{CHi} = \sqrt{\frac{\sum dis^2}{n}}$	(4)
Here, the term $\sum dis^2$ is summation for squared distances of nodes with CHs i. N =no. of nodes within a cluster	
$\text{Node degree} = \text{var} \left\{ \frac{(\text{no. of nodes in Cluster } i)}{\text{total no. of nodes in network}} \right\}$	(5)
If E_{TX} or E_{RX} consumed energy in a round in a transmitter or receiver a packet, then:	
E_{res} for r round: $E_{res}(r) = E_{res}(r-1) - E_{TX \text{ or } RX}$	(6)
Fitness function= $F = f(1/f_1, f_2, 1/f_3, 1/f_4, 1/f_5, f_6)$ and Scale factor={a1 to a6}	
$\text{fitness value} = \sum_{i=1}^6 F_i \times a_i = 1/f_1 \times a_1 + f_2 \times a_2 + 1/f_3 \times a_3 + 1/f_4 \times a_4 + 1/f_5 \times a_5 + f_6 \times a_6$	(7)

Table 2. CH Selection algorithm using GWO with ASWDR data compression.

GWO EAC ASWDR
Define:
1. n =no. of nodes
2. random positions of n nodes
3. sink node fixed position
4. $E_{TX/RX}$, $E_{initial}$, $E_{amplifier}$, $E_{aggregating}$
5. $D_{threshold}$, Max. Round
$I=1$ to n (for Loop)
6. randomly allotment of advanced energy
7. $E_{initial}(i) = E_{initial} * (1 + R * a) \% R$ =random value
8. Alloting G flag
end (For Loop)
9. Setting Count_{CH} , Flag all dead, Flag first dead, $N_{dead \text{ nodes/alive nodes}}$, $\text{Packet}_{sent \text{ to CH or BS}}$

For Loop r: 1 to Max. Round

10. If $(\text{mod}(r, \text{round}(1/P)) = 0) \% \text{reset G flag on } 1/p \text{ rounds}$
11. Reset $G(i)=0$
if condition end
12. Checking :dead nodes count
13. Checking: 1st node dead & set $\text{Flag}_{\text{first dead}}$
14. Checking: All nodes dead & set $\text{Flag}_{\text{all dead}}$
15. Checking: energy of ith Node $E_i > 0$ % node alive or not
16. Defining GWO parameter: [pop, iter] % {population size, iteration}
17. Run GWO algorithm
18. Finding best set of CH id : CH_{best} by GWO
19. Finding nearest nodes to CH
20. Allotment of CH to nearest nodes
21. Transmission of Data from nodes to CH
22. Calculation of Energy in data S to CH transmission
23. Counting no. of packets sent from CH to BS
24. Perform aggregation of data at CH.
25. Compression of data at CHs by ASWDR.
26. Transmission of Compress data through CH to BS
27. Calculation of Energy in transmit of packet at CH to BS
28. Counting no. of packets sent from CH to BS
29. $E_{\text{res}}^{i,r} = E_{\text{res}}^{i,r-1} - \text{Energy Consumes to CH or CH to BS}$ % Calculation of residual energy of node ith at round rth end of for loop

Algorithm Description (GWO)

Each wolf represents a set of CH ids:

$$X = \{b_{t,r}, c_{t,EV}, R_{\text{schedEV}}(t)\}$$

Leadership Hierarchy:

- α (Alpha) $\rightarrow$ Best DSM solution (minimum D_{peak})
- β (Beta) $\rightarrow$ Second best
- δ (Delta) $\rightarrow$ Third best
- ω (Omega) $\rightarrow$ Remaining candidate solutions

GWO mimics **grey wolf hunting behavior**, where wolves:

- Encircle the prey (optimal solution)
- Update positions using leaders
- Transition from exploration to exploitation gradually

Step 4: Position Update

For each wolf:

$$D_{\alpha} = |C_1 \cdot X_{\alpha} - X|$$

$$D_{\beta} = |C_2 \cdot X_{\beta} - X|$$

$$D_{\delta} = |C_3 \cdot X_{\delta} - X|$$

$$X_{t+1} = (X_1 + X_2 + X_3) / 3$$

where:

$$X_1 = X_{\alpha} - A_1 \cdot D_{\alpha}$$

and A_k, C_k depend on the control parameter a .

Step 5: Constraint Handling

- Enforce EV charging, solar, and load constraints.

Step 6: Update Parameter

$$a = 2 - (2t / \text{Iter}_{\text{max}})$$

Step 7: Termination

- Stop at convergence or maximum iterations.

Here, the values of the overall parameters f_1 to f_6 have differences in range; hence, they are normalized to bring them under an equal range by multiplying the scale factors a_1 to a_6 to maintain equal weightages for all the parameters.

Grey Wolf Optimization (GWO)

GWO is a nature-inspired optimization technique that simulates the social hierarchy and cooperative hunting strategies of gray wolves in the wild. In this algorithm, candidate solutions are treated as wolves, and the process of finding the optimal solution is analogous to wolves hunting prey. The population is divided into four categories: alpha, beta, delta, and omega, where alpha represents the best solution, followed by beta and delta as the next best solutions, and the remaining are omega wolves. These top three wolves guide the search process and influence the movement of the other wolves toward promising regions of the solution space.

The GWO works through iterative position updates based on the mathematical modeling of encircling, hunting, and attacking prey. Initially, a set of random solutions is generated, and their fitness is evaluated. During each iteration, the positions of the wolves are updated with respect to the alpha, beta, and delta wolves, which helps approximate the global optimum. The algorithm balances exploration and exploitation using adaptive coefficient parameters, allowing it to search widely in the early stages and gradually converge toward the best solution.

This mechanism helps avoid local optima and improves the convergence accuracy. Because of its simplicity, fewer control parameters, and efficient performance, the GWO is widely applied in engineering optimization, machine learning, and control system problems.

Distributed Energy-Efficient Clustering (DEEC)

The DEEC is a dynamic clustering protocol developed for heterogeneous WSNs. Unlike traditional approaches that assume a uniform energy distribution, DEEC adaptively determines the probability of each node becoming a CH based on its residual energy and the average network energy. Nodes with higher energy levels are assigned a greater probability of serving as CHs, which helps balance energy consumption across the network. This mechanism prevents weaker nodes from being overburdened and improves both the stability period and overall network lifetime.

Additionally, the DEEC operates in a distributed manner, allowing each node to independently decide its role without requiring global network knowledge. The protocol is further adapted over time by recalculating energy-related parameters in each round to ensure the optimal utilization of available resources.

Adaptively Scanned Wavelet Difference Reduction (ASWDR)

ASWDR has the quality of a lossless compression technique that depends on wavelet-based image coding. It shows improvement over the previous methodologies, such as Embedded Zerotree Wavelet (EZW) and Set Partitioning in Hierarchical Trees (SPIHT). The ASWDR effectively encodes important wavelet coefficients using adaptive scanning and difference reduction to exploit their sparsity after transformation. Adaptively scanning modified data prioritizes blocks with significant information and optimizes bit resources. The main aim is to reduce major wavelet coefficient discrepancies and estimate their values using a geographical context to improve compression and data integrity.

This study adds the GWO algorithm for CH selection to the DEEC procedure. As shown in Figure 1, the yellow squares represent the global best solution, blue circles represent stray nodes (possible solutions), and red circles represent the current solution at (x_i, y_i) that needs updating. The node with the largest residual energy in the optimum triangular search space is $(X_i, Y_i)_{\text{new}}$. The optimization is guided by the distance between current node location and global optimal position. The square bounds given by the coordinates $[(x_{\min}, y_{\min}), (x_{\min}, y_{\max}), (x_{\max}, y_{\min}), (x_{\max}, y_{\max})]$ are the furthest search limits from the current best solution and correspond to the CH set of the global best solution. Figure 2 shows wolves as groupings of sensor nodes picked randomly and updated depending on greater fitness values in the search space. The GWOEACASWDR protocol combines GWO with DEEC to create GWO-based Energy-Aware Clustering (GWOEAC) and adds ASWDR-based data compression.

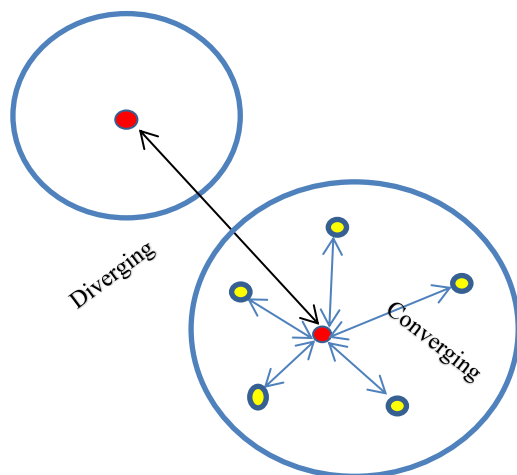


Figure 1. Diagram schematics for demonstration of the clusters for describing the concept of diverging and converging functions.

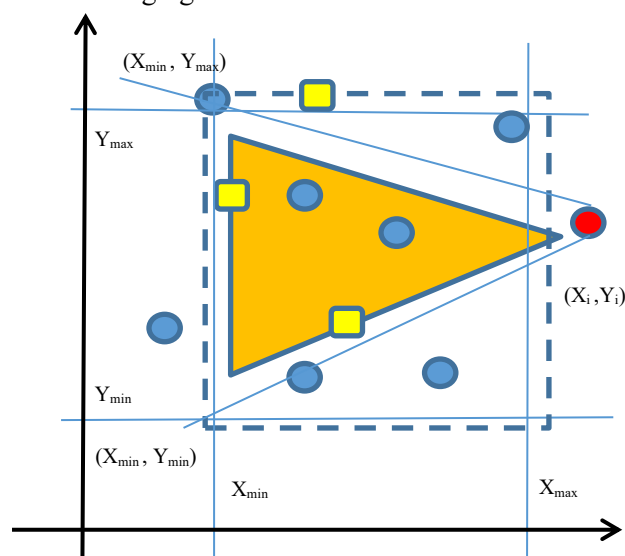


Figure 2. Diagram depicting the approach for update of next cluster head for getting better solution.

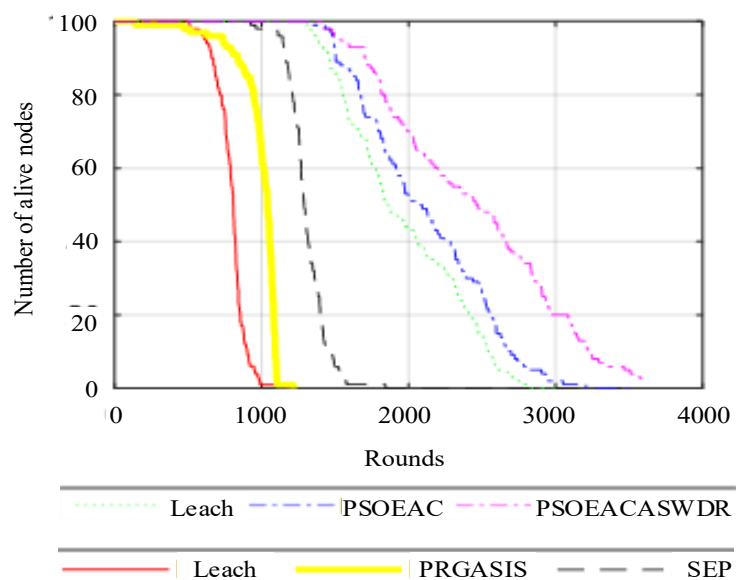


Figure 3. Alive nodes Variation wrt rounds under WSN protocols within IoT application.

RESULTS

MATLAB 2019 simulates WSN routing using the proposed protocols, GWOEAC and GWOEACASWDR, which transfer data from source nodes to the BS through an optimal set of cluster heads. The simulation parameters include a 4000-byte packet size, a $100 \times 100 \text{ m}^2$ network field, and 100 sensor nodes. Typical WSN radio model factors include energy consumption during transmission and reception, data aggregation energy, and route loss models, such as free space and multipath fading. Multiple rounds of simulations are conducted until all the sensor nodes run out of energy. The system performance was measured by the number of living nodes, packets sent from sensor nodes to CHs, packets sent from CHs to the BS, and energy consumption per transmission. Other routing protocols, including LEACH, PEGASIS, SEP, and DEEC, were simulated for comparison. Figure 3 illustrates the number of active nodes throughout the simulated rounds for the different protocols. GWOEAC and GWOEACASWDR have longer operational lifetimes than DEEC and SEP, whereas LEACH has the shortest.

Figures 4 and 6 show that a longer lifespan increases data transmission between nodes and CHs and CHs to the BS. The energy usage per transmission depends on the communication distance and packet count, as shown in Figure 5. The GWO optimizes CH placement to decrease the transmission distance, whereas the ASWDR-based compression reduces the packet size and energy usage by 40–50%. The boxplot in Figure 5 displays the minimum, maximum, and average energy levels, showing that the proposed strategy uses the least energy. Tables 3 and 4 summarize these results by statistically comparing energy use and packet transmission. The GWOEACASWDR protocol uses the least amount of energy and transmits the most packets during its lifespan.

Table 4 lists the round values for the first node dead, half of the nodes dead, 90% depletion, and full node failure. The stability period begins at round 14011, and the network lifespan ends at round 3626 for the proposed protocol.

Table 5 compares the proposed methodology with contemporary IoT approaches, notably data compression and routing methods, to verify its efficacy. This study integrates optimization and data compression approaches, which have not been used in the literature, to improve IoT applications in WSN contexts. Using the compression ratio (CR), the suggested ASWDR-based approach was compared to Khafaga, Hosny, and Bencherqui's research on data compression. The proposed approach has a CR of 42%, whereas others claim 15% to 25%. In addition, energy-efficient routing methods such as EGRPM, RRP, and PRVD are compared [18]. The results demonstrate that the proposed method uses the least amount of energy, outperforming existing methods.

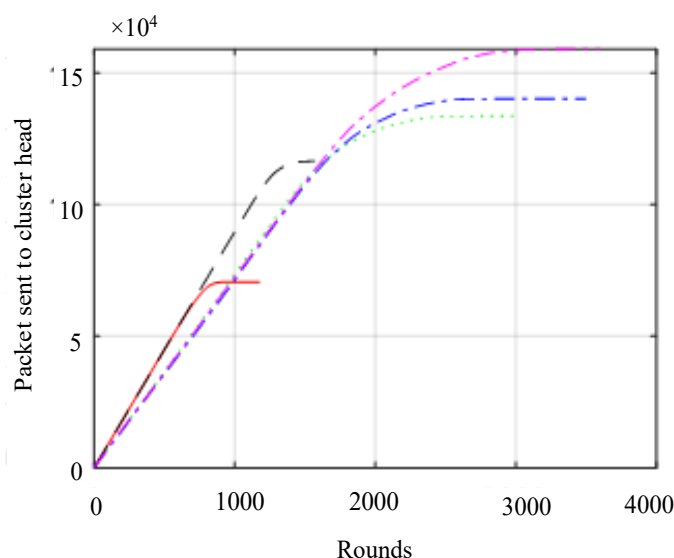


Figure 4. Packets sent to CH wrt rounds for different WSN routing protocols under IoT environment.

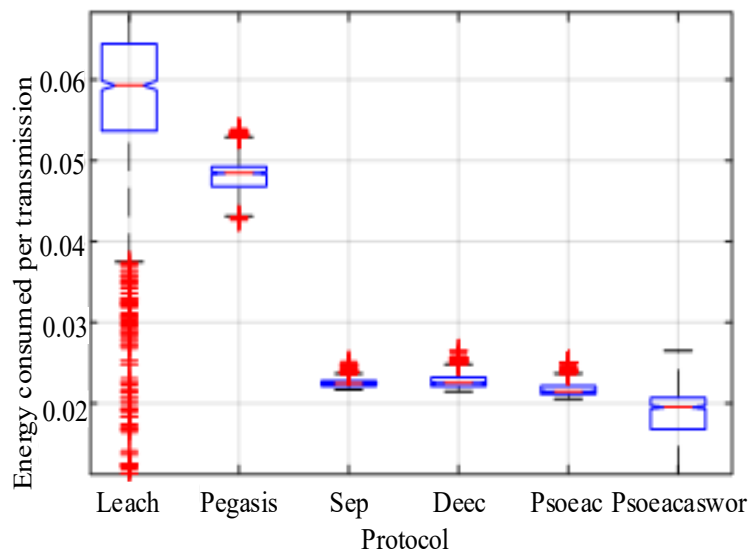


Figure 5. Distribution of energy consumed per transmission for IoT networks of WSN environment routing protocols.

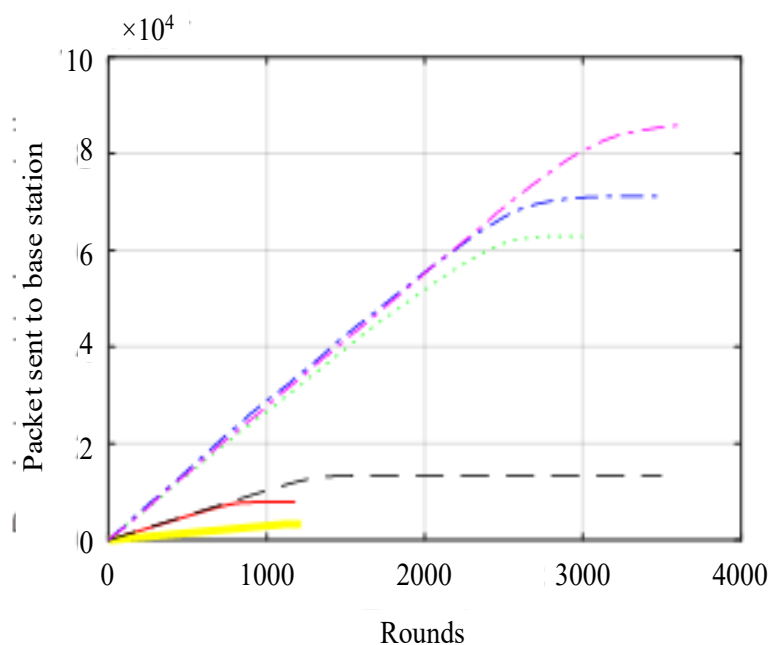


Figure 6. Packets sent to BS wrt rounds for IoT network WSN routing protocols environment.

Table 3. Statistical analysis of energy consumption and packet transmission under different IoT network routing protocols in a WSN environment.

Energy consumption in each transmission (in Joules)	LEACH	PEGASIS	SEP	DEEC	GWO, EAC, ASWDR
Avg. value	0.0554	0.0485	0.0224	0.0227	0.0182
Std. deviation	0.0176	0.0024	0.0005	0.0008	0.0037
Variance	3.1×10^{-4}	6.1×10^{-6}	2.8×10^{-7}	7.7×10^{-7}	1.3×10^{-5}
Total packets sent					
Node to CH	70670	Not applicable	116400	133600	159100
CH to BS	7914	3378	13420	62930	85790

Table 4. Performance analysis of network lifetime.

	1 st Dead	Half Dead	90% Dead	Last Dead
LEACH	508	807	903	1175
SEP	924	1289	1462	1842
PEGASIS	141	1039	1092	1216
DEEC	1307	1860	2550	2811
GWOEAC	1348	2091	2698	3226
GWOEACASWDR	1411	2471	3206	3626

Table 5. Comparison of the performance of the proposed work GWOEACASWDR to recent methods.

Comparison of Proposed Methods for Compression Ratio Measurement		
Method	Author (Year)	CR
Haar wavelet-based block transforms and COVIDOA	Khafaga et.al (2023) [18]	25.623%
GWOEACASWDR	(Proposed)	42.012%
Comparison of Proposed Methods for Average Value of Consumption of Energy		
Method	Author	Avg. energy consumption
PRVD	Elyyan et.al. (2023) [19]	.02103
GWOEACASWDR	(Proposed)	.01805

CONCLUSIONS

The lifespan and efficiency of WSNs can be improved using a GWO-based energy-efficient multipath routing protocol. Selecting the most energy-efficient combination of optimum nodes as CHs from a pool of options extends the network lifespan. The GWO analyzes sophisticated criteria, including node location, communication distance, and residual energy, to obtain the best CH IDs. An ideal set of high-fitness nodes is selected to reduce the network energy usage. ASWDR-based data compression reduces the packet size and energy use during CH-BS communication, improving WSN-enabled IoT applications under the GWOEACASWDR architecture. Reducing the routing burden, increasing the throughput, and decreasing the packet loss improve the QoS. Simulations show that the suggested technique considerably extends the WSN operating lifespan. Comparative research shows that GWOEACASWDR outperforms SEP and DEEC. Overall, the routing method supports real-time, reliable IoT applications with ensured QoS. Further research may integrate the GWO algorithm with existing routing strategies to address large-scale routing difficulties in hybrid sensor network systems.

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