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HYBRID WHALE-GREY WOLF OPTIMIZER FOR ADAPTIVE CLUSTER HEAD SELECTION AND ENERGY CONSERVATION IN WIRELESS SENSOR NETWORKS

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SUMMARY

WSNs are critical to the contemporary IoT and monitoring, yet the energy constraint, inefficient performance of cluster head (CH) selection, and fluctuating routing diminish the network lifetime and reliability. This paper will introduce a solution to these issues by proposing a Hybrid Whale -Grey Wolf Optimizer (HWGWO) to select the adaptive and energy-efficient CH. The goal is to improve the energy balance, delivery of data, and stability of the network by integrating the global exploration capacity of the Whale Optimization Algorithm (WOA) and local exploitation capacity of the Grey Wolf Optimizer (GWO). The approach is based on a two-stage optimization strategy and multi-objective fitness that takes into account residual energy, communication distance, and load balancing. The suggested model is simulated in MATLAB and NS-2, and 100 nodes are placed in a 200 m by 200 m network. The simulation findings prove that HWGWO is more efficient than current protocols like EPSO-CEO and LEACH. The suggested strategy has a high Packet Delivery Ratio (PDR) of up to 99.20, a low normalized routing overhead (NRO) of 0.98, and a delay of 0.012s. It also reduces the ratio of packet drop to 0.033% and increases the throughput to 120,000 bps. Moreover, HWGWO minimizes the total energy expenditure to 10.5 J (approximately 3 % decrease) and keeps the residual energy (208.5 J) higher, thus increasing the network lifetime. Generally, HWGWO offers an efficient solution to energy-efficient clustering and dependable communication within the WSNs.

Key words: *wireless sensor networks (WSN), energy efficiency, cluster head (CH) selection, hybrid metaheuristics, whale optimization, grey wolf optimizer (GWO), MATLAB simulation, network lifetime.*

INTRODUCTION

The (HWGWO) is a superior optimization methodology that integrates the merits of two powerful meta-heuristic methods (WOA) and the Grey Wolf Optimizer (GWO) to promote adaptive cluster-head (CH) selection and energy saving in Wireless Sensor Networks (WSNs) [1][3][9]. Clustering is a common technique for reducing power consumption; it entails grouping nodes into clusters and having a CH aggregate and transmit data [21][31][32]. However, inefficient clustering and energy imbalances might result from traditional CH selection procedures [12][18][25]. In order to minimize the time spent choosing a CH, the HWGWO algorithm is used, taking into account the node energy, communication distance, and network topology issues [11][14]. The combination of WOA's exploration capabilities with GWO's exploitation capabilities allows HWGWO to outperform both in terms of energy efficiency and the longevity, stability, and reliability of the network [6][23]. The hybrid solution is especially applicable in energy-harvesting WSNs (EH-WSNs) where the energy sources are intermittent and need adaptive and intelligent energy management solutions [19][27]. The balance achieved by the HWGWO algorithm between exploration and exploitation makes it a very effective solution to dynamic and energy-constrained environments, and it is thus a promising tool in a modern WSN application [4][7].

The following are a few of the benefits of clustering. (1) By doing so, it may integrate the data level and [10] reduce the network's energy usage without transmitting separate data from each sensor node [5]. (2) The network's scalability is greatly enhanced. (3) Since the sensor nodes won't be interacting with each other, there's less strain on the network's communication capacity. Consequently, choosing the right CHs during the clustering exercise is crucial for the network's lifespan [13][15][17]. Nonetheless, due to the various impacts on member sensor node energy conservation, the selection of CHs in the clustering exercise is highly critical for the life span of the network. As such, the selection process must take time when selecting the CHs. CH-selection is a non-polar optimization problem, according to [16][20][22]. Optimizing a network of a large size becomes less efficient using conventional methods. A new Hybrid Whale-Grey Wolf Optimizer (HWGWO) to select CHs in WSNs that consume less energy and adaptive clustering are proposed in this study as an example of nature-inspired techniques that can be a more suitable choice in such NP-hard problems [33]. To perform the comparative simulations with EPSO-CEO, LEACH, and HEED to ensure that the proposed model actually does enhance the energy efficiency and network lifespan.

Motivation

Many improved and changed versions of the LEACH protocol have been created to keep the network running longer after the original LEACH protocol stopped working well. However, most of these attempts did not successfully reduce energy use, which directly impacts how long the network can last and how stable its energy is. At that point, it was decided that a reliable cluster-based routing protocol using swarm intelligence, which is inspired by nature, was more likely to keep the sensor nodes' energy stable for a longer time.

The Major Key Contribution of this Research is as Follows,

- To optimize Cluster Head (CH) selection in WSNs, a novel Hybrid Whale-Grey Wolf Optimizer (HWGWO) is proposed, combining the search capability of WOA with the exploitation strength of GWO.
- For improving multi-hop routing efficiency, HWGWO determines the best CH combinations to reduce energy consumption while maintaining dependable data transmission.
- To select the cluster, an efficient dynamic head selection approach is used.
- To balance network performance, a MOFF is designed considering load balancing, residual energy, and inter-cluster distances.
- While differentiating from existing approaches, the proposed approach outperforms existing approaches.

Paper organization: Section 2 reviews recent CH-selection and energy-aware clustering approaches and highlights the remaining research gap. Section 3 states the problem addressed by adaptive energy-aware clustering. Section 4 details the proposed HWGWO framework, including the network/energy models, fitness function, and the hybrid WOA–GWO search strategy. Section 5 presents the implementation details and provides the complete pseudocode. Section 6 reports and analyzes the simulation results, including an ablation analysis. Section 7 discusses practical implications and limitations, and Section 8 concludes the paper with future directions.

LITERATURE REVIEW

Recent research shows that metaheuristic cluster-head (CH) selection can significantly improve energy balance and network lifetime compared with purely probabilistic protocols such as LEACH. Swarm- and evolutionary-based schemes optimize CH placement using residual energy, distance, and load objectives, typically reporting longer stability periods and reduced packet loss under dense deployments. However, many single-algorithm approaches still face an exploration–exploitation trade-off: strong exploration may delay convergence, while strong exploitation can stagnate in local optima and yield suboptimal CH sets when topology or traffic changes.

Hybrid metaheuristics have therefore been proposed to combine complementary search behaviors. Inference from the recent literature indicates that hybrids generally outperform their individual components when (i) the CH-selection space is discrete/binary, (ii) node energy becomes heterogeneous over rounds, and (iii) the network requires stable clusters to limit control overhead. Nevertheless, two practical gaps remain: (1) many studies do not explicitly control the switch from exploration to exploitation, leading to inconsistent performance across scenarios, and (2) several papers report only limited metrics without jointly analyzing reliability (PDR), delay, throughput, and routing overhead under a consistent simulation setup.

To address these gaps, this work proposes HWGWO, which uses WOA for early global exploration and GWO for late-stage exploitation with an explicit switching strategy. The method is evaluated using a unified experimental setup and a full set of WSN performance metrics.

Based on a modified version of the GWWOA, Reddy et al. [34] suggested a strategy for cluster routing. This approach selects the best cluster head (CH) using energy, security, latency, and distance as multi-objective criteria. To find the best CH to explore and exploit within the constraints of energy and distance, Nagarajan & Thangavelu [24] presented HGWSFO, a combined algorithm using the two methods. Taking into account both the number of nodes and their distances, Shah et al. [35] developed the mixed grey wolf and enhanced sunflower optimisation method (MGWISFO). This method chooses the best network for exploration and exploitation, therefore improving network performance. The IQ-ABC method, developed by Alsuwat & Alsuwat [26]. It is used between CH selection processes. Using the Euclidean distance to group nodes and subsequently pick the CH in a group, SWARAM, developed by Somula et al. [2], is an alternative method to energy-efficient CH selection in IoT-based WSNs. When comparing the LEACH technology, in particular in a mobile node context, to a model proposed by Jalili et al. [28], the authors advocate using residual energy as a selection metric to ascertain the optimal placement of CH in a WSN using the trained neural network model (MLPs). El Khediri et al. [29] applied the ant colony optimization (ACO) and artificial bee colony (ABC) to improve the work of the WSN by considering the node degree, centrality, distance to the neighbors, and base station. To optimize multi-objective to assist in enhancing data delivery, reducing energy consumption, and enhancing network lifetime, Wilson et al. [30] designed the EACHS-BzSpNNsinglebondHBA-WSN structure. This framework involves the Honey Badger Algorithm and Binarized Spiking Neural Networks with the selection of the CH.

The literature demonstrates that the hybrid metaheuristic methods achieve better energy efficiency, network lifetime, and reliability in WSNs than the conventional methods. But the methods available do not adequately control the exploration-exploitation balance, and they fail to measure all the important key performance indicators. The proposed HWGWO can help to fill these gaps by offering an adaptive hybrid approach with a detailed performance assessment, which guarantees improved and more reliable CH selection.

PROBLEM STATEMENT

The partial energy of sensor nodes can cause problems for a WSN, as it can affect how well the network works, like how long it lasts and how well it sends data. Some methods like LEACH and HEED have been used to help with energy use, but it has their limits. Algorithms like (PSO) and (WOA) are examples of nature-inspired methods that have shown to improve energy efficiency. The hybrid types like PSO-GWO and GA-WOA are more computationally efficient and have a better energy balancing performance. However, there is still a need for a flexible clustering method that can adapt to changing network conditions. The proposed Hybrid Whale-Grey Wolf Optimizer (HWGWO) aims to make clustering more responsive and improve energy efficiency, data transmission, and the overall life of the network by enhancing cluster head selection.

PROPOSED METHODOLOGY

This part goes into further detail on how the Hybrid Whale-Grey Wolf Optimizer (HWGWO) was systematically designed to choose adaptive (CHs) in (WSNs). The suggested architecture is based on three main parts: the network model, the energy model, and a hybrid clustering method that uses the Whale Optimization method (WOA) to find new solutions and the (GWO) to improve existing ones.

Network Model

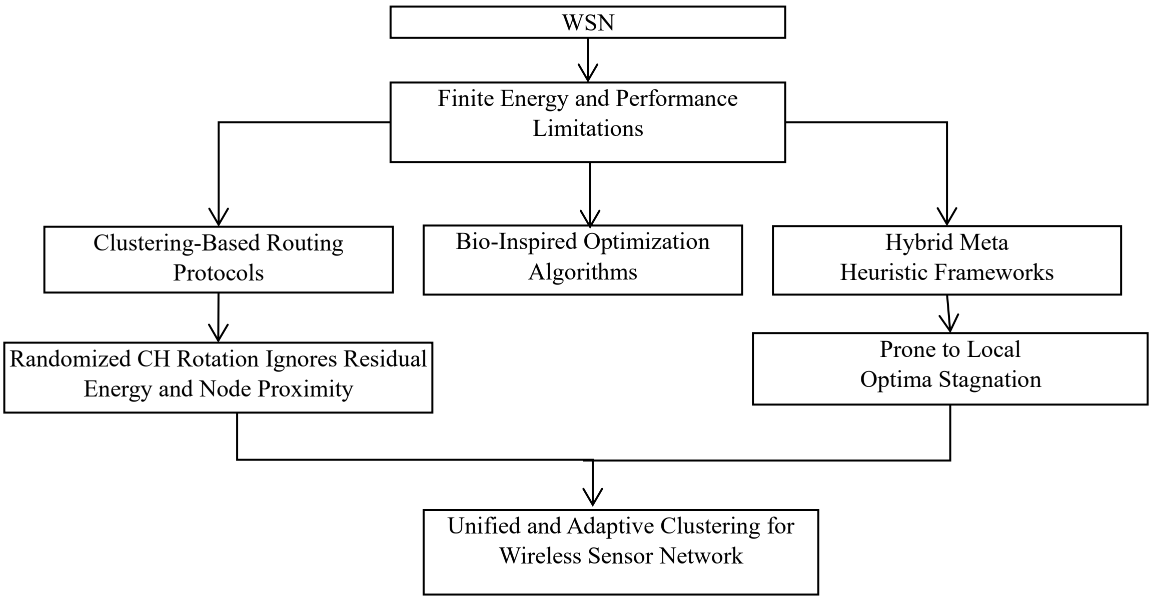

Figure 1. Overview of the proposed HWGWO-based energy-aware clustering workflow and decision stages

The figure 1 summarizes the pipeline: network/energy modeling, candidate CH generation, fitness evaluation, WOA-driven exploration, GWO-driven exploitation, and final CH selection with energy-aware (single-/multi-hop) forwarding.

To suppose that the proposed system consists of a fixed WSN consisting of sensor nodes, which are identical, and are distributed randomly across a 2D region of size LxL. A base station (BS) is installed at the edge or in the middle of an area that is being monitored. Each sensor node can sense, process, and connect, and all begin with the same amount of energy E_0.

What to think:

- After that is put in place, sensor nodes stay the same.

- Each node also knows its location and can approximate its distance to other nodes and the base station (BS).
- CHs collect information from their members and send it to the BS directly or through many hops.
- Links of communication are the same on both ends.

From the equation below, equation (1) describes that each node i has its coordinate point(x_i, y_i), and the Euclidean distance d_{ij} between node i and node j is determined by:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (1)$$

Energy Model

The First Order Radio Model [8] is the basis for the energy model utilized in this work. It takes into account the energy needed to send and receive data. Free Space (when $d < d_0$) and Multipath Fading (when $d \geq d_0$) are the two models utilized for propagation.

The amount of energy needed to send a l -bit message over a distance d is:

$$E_{TX}(l, d) = \begin{cases} lE_{elec} + l\varepsilon_{fs}d^2, & d < d_0 \\ lE_{elec} + l\varepsilon_{mp}d^4, & d \geq d_0 \end{cases} \quad (2)$$

From the above equation (2) describes,

- $E_{elec}$is the amount of energy needed to run the transmitter or reception electronics for each bit.
- ε_{fs} and $\varepsilon_{mp}$and are the amplification factors for the free space and multipath models.
- $d_0 = \sqrt{\varepsilon_{fs}/\varepsilon_{mp}}$

The amount of energy needed to send a l -bit message is:

$$E_{RX}(l) = lE_{elec} \quad (3)$$

Equation (3) describes adding up data at the CH uses more energy:

$$E_{DA}(l) = lE_{DA} \quad (4)$$

Equation (4) describes the energy needed to combine data per bit.

Mathematical Preparation of Energy Consumption

The First Order Radio Model is used to compute the energy consumption for transmitting and receiving messages in a Wireless Sensor Network (WSN).

$$E_{Tx}(k, d) = \begin{cases} kE_{elec} + k\varepsilon_{fs}d^2, & d < d_0 \\ kE_{elec} + k\varepsilon_{mp}d^4, & d \geq d_0 \end{cases} \quad (5)$$

$$E_{Rx}(k) = kE_{elec} \quad (6)$$

$$E_{DA} = kE_{DA} \quad (7)$$

The circuit of Energy expended (Receiver and Transmitter) is represented as E_{RX}, E_{elec}Depicting the power used by the circuit in transmission and receiving. The factors of energy of the Amplifier are expressed as ε_{fs}, ε_{mp}, The free-space and multipath energy parameters are respectively, which are the free-space and multipath energy parameters. The Threshold distance $d_0 = \sqrt{\varepsilon_{fs}/\varepsilon_{mp}}$ (Equation 5) is the distance at which the energy model changes between free-space propagation and multipath propagation. The Packet size is represented by k, meaning the size of the data packet in bits, and the Distance between the sender and recipient is denoted by d. The above parameters are used to explain the energy required during transmission and reception in equations (6) and (7).

The Hybrid WOA-GWO Clustering Algorithm

The (HWGWO) uses the best parts of both WOA and GWO. It combines the exploration behavior of WOA in the first stages with the phase of GWO in the last stages of the process. The goal is to choose the best set of cluster heads while using the least amount of energy overall.

Starting Up

Let the location of each search agent (particle) be a candidate CH configuration vector $X_i = [x_1, x_2, \dots, x_N]$, where $x_j \in \{0,1\}$, shows if node j is a CH. The number of search agents is set up at random.

Multi-Objective Fitness Function (Improved Presentation)

The fitness of each candidate (Equation 8) cluster head (CH) configuration is determined using a MOF that balances residual energy, intra-cluster distance, and load distribution:

$$f(CH_i) = w_1 \frac{E_{res}(CH_i)}{E_{max}} + w_2 \left(1 - \frac{d_{CH_i,avg}}{d_{max}}\right) + w_3 \left(1 - \frac{\sigma_{load}}{\mu_{load}}\right) \quad (8)$$

The parameters in the multi-objective fitness function of selecting cluster head are defined in equation (8). E_{res} represents the residual energy of the cluster head, while E_{max} indicates the maximum energy across all nodes in the network. $d_{CH_i,avg}$ is the average distance within a cluster and refers to the maximum communication range. σ_{load} is μ_{load}, the standard deviation and mean of the size of clusters, respectively. The weight coefficients w_1, w_2, w_3 set to 0.4, 0.3 and 0.3, weight the three objectives in the fitness function.

Exploration Based on WOA

In WOA, agents change their location utilizing a spiral mechanism that works like how bubble-net hunters move. The position update during the exploring phase is:

$$X(t+1) = D \cdot e^{bl} \cdot \cos(2\pi l) + X^* \quad (9)$$

Equation (9) describes about

$$D = |C \cdot X^* - X(t)| \quad (10)$$

Equation (10) describes

- $X^*$is the finest place to be right now,
- bandlare numbers that stay the same and regulate the curvature of the spiral.

Using GWO for Exploitation

GWO puts the best three candidate solutions in order: alpha, beta, and delta wolf. Other agents change their rank depending on how much these top candidates affect them:

$$X(t+1) = \frac{X_\alpha + X_\beta + X_\delta}{3} \tag{11}$$

$X(t+1)$ Revised position of the search agent. $X_\alpha + X_\beta + X_\delta$ Positions of the best (alpha), the second-best (beta), and the third-best (delta) solution. In this equation (11), each agent is updated by averaging the top three solutions, which directs the search to the regions of optimality.

$$X_\alpha = X_{\alpha'} - A_1 \cdot |C_1 \cdot X_{\alpha'} - X|, \tag{12}$$

Equation (12) describes, A and C are coefficient vectors that change over time to find the right balance between exploration and exploitation.

Update of Position and Convergence

After a certain number of repetitions, Tswitch, the hybrid system changes from WOA to GWO. The position of the search agents is updated at each iteration, and the best solution is saved.

Adaptive CFDR

Following the selection of optimal CHs, sensor nodes will join the CH that is geographically or RSSI-based nearest to them. The data is aggregated before it is sent to the BS by the CHs. This can either be done by means of a single-hop or multi-hop communication based on the distance between the base station (BS) and the leftover energy. This hybrid model improves energy balance, network longevity, and data delivery efficiency by fixing the problems with both traditional and single-technique metaheuristics.

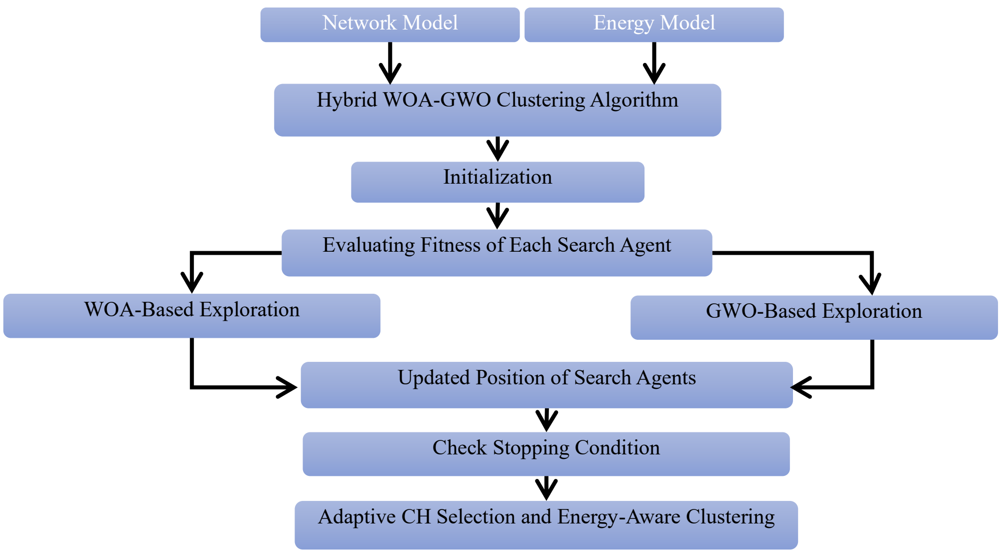

Figure 2. The steps in the proposed hybrid WOA-GWO clustering algorithm for choosing CHs in WSNs that are aware of energy use

This figure 2 explains how a Hybrid (WOA) is combined with (GWO) to address issues relating to the optimization of energy on a network. The first step has 2 parameters to put into the system: the Network and the Energy. These will define the conditions for the optimization to be carried out. The approach sits on the hybridization of WOA and GWO, which are algorithms based on natural phenomena. One of them, WOA, is based on the stalking style of whales, while GWO imitates the social structure and the tactics in hunting of a pack of wolves. The first of these algorithms is used to simulate a solution space. This solution space reflects the configuration of a network and the associated parameters for the management of energy. Candidate solutions are generated to represent the various potential network structures. Then, the solutions are evaluated for their fitness, and GWO and WOA approaches are used in tandem to do that. WOA simulates various hunting behaviours of whales to estimate a solution's fitness while GWO organizes the solutions based on a pack structure and a hierarchical leadership approach. After the solutions are weighted for fitness, their positions in the solution space are updated. The solutions are guided toward a better zone of the solution space. WOA encourages movement with whale based behavioural simulation and GWO provides wolf-based movement that tries to mimic hunting. At this point, the algorithm checks for defined stopping criteria such as the number of iterations or convergence toward a solution. After the stopping condition has been met, the algorithm selects the adaptive Cluster Head (CH), which guarantees the optimal network configuration. This final selection of the adaptive CH guarantees that the network configuration is at the optimum energy level.

IMPLEMENTATION AND ALGORITHM

The Hybrid Whale-Grey Wolf Optimizer (HWGWO) clustering algorithm was modeled in MATLAB, where potential network emulation could be done in NS2/ NS3. The system works in a 2D space of 200X200 meters and it represents a (WSN) where sensor nodes are introduced with prearranged amount of energy. HWGWO is population based and it chooses a population of cluster heads (CHs) with fitness being determined by the residual energy, the closeness within the cluster and load balancing. The algorithm starts with WOA to do general exploration and switches to GWO to accomplish local optimization. The positions of the agents are changed until convergence, and the best CHs are selected and allocated to create balanced clusters. Information is relayed to the base position through a single-hop or a multi-hop. HWGWO performs better than the baseline algorithms, such as LEACH and EPSO, in network lifetime, energy consumption, and communication performance, which provides adaptive clustering to enhance energy consumption and network sustainability.

Simulation Setup and Dataset Specifications

Table 1. Simulation parameters and setup for HWGWO algorithm evaluation in wireless sensor networks

Parameter	Description / Value
Simulator	MATLAB R2023b, NS-2.35
Topology	200 m × 200 m square field
Node count	100 (homogeneous)
Initial energy	3 J per node
Base station	(100 m, 250 m) (outside field)
Packet size	512 bytes
MAC / PHY	IEEE 802.11 / Free-space model
Simulation time	200 s
Rounds tested	50 – 200
Reference models	EPSO-CEO, LEACH
Metrics	PDR, Throughput, Energy Consumption, Delay, NRO, Residual Energy, Lifetime
TE (Transmit Energy)	0.02 W
RE (Receive Energy)	0.01 W
PM (Propagation Model)	Two-Ray Ground

The table 1 presents the major simulation parameters of analysing the Hybrid Whale-Grey Wolf Optimizer (HWGWO) in Wireless Sensor Networks (WSNs). It contains the description of the simulating environment, network topology, node configuration, and performance indicators such as PDR, throughput, energy consumption, and delay. Energy values of transmission and reception, the propagation model utilized, are also discussed in the table that gives a complete overview of the experimental setup and comparison models (EPSO-CEO, LEACH).

A Dynamic Cluster Head Selection

The proposed dynamic method for selecting CH in a circular (WSN) would improve energy efficiency by shortening the data transmission distance to the sink node. The network will be separated into several levels, and the nodes will be randomly spread across every level. Then (WOA) is used to narrow down the choice of the most optimal cluster heads at each round. In WOA, the search agents (whales) are put in a 2-D space, and the location of the optimum agent defines the optimum cluster head. The fitness in WOA considers the remaining energy in the node in question as well as that of its neighbors to select the most efficient cluster heads. The approach maximizes the network lifespan while reducing energy consumption by randomly selecting cluster heads every round and minimizing data delivered to the sink.

The fitness function is given by,

$$f(CHi) = p1(CHi)(CHe) + \sum p2N(CHi) \tag{13}$$

Equation (13) reveals that $p1$ might be zero or one, depending on the node chosen as the cluster leader. CHi is the neighboring node's outstanding energy level. The probability that a cluster head node N has neighbors in the spiral region is denoted as $p2$. The suitability function value is affected by the total neighbor count. Having sufficient residual energy and enough neighboring nodes to create a new bunch head determines the optimal response, which is the one with the greatest fitness value.

Algorithm: Hybrid WOA-GWO-Based Clustering for Choosing CHs That Use Less Energy

Algorithm: HWGWO-based clustering for energy-aware CH selection

Input: N nodes; MaxIter; PopSize; initial energy E0; field size L×L; BS location; radio parameters

Output: CH set and cluster assignment for each node

```
Deploy N nodes randomly; initialize E(n)=E0
Initialize PopSize binary CH vectors (search agents)
Evaluate fitness F for each agent using energy–distance–load objectives
X* ← best agent; Tswitch ← ⌈0.5·MaxIter⌉
for t = 1 … MaxIter do
  for each agent X do
    if t ≤ Tswitch then  // WOA exploration
      Update X using WOA encircling/spiral equations; binarize (threshold)
    else               // GWO exploitation
      Determine α, β, δ (top-3 agents); update X using GWO rules; binarize
    end if
    Enforce feasibility (CH bounds, uniqueness)
    Recompute F(X); if F(X) > F(X*) then X* ← X
  end for
end for
Select CHs where X*[i]=1; assign remaining nodes to nearest/strongest CH
Aggregate data at CHs; forward to BS using energy-aware single-/multi-hop routing
Return CH set and cluster map
```

In the beginning, this algorithm uses WOA to explore the whole network, and subsequently it uses GWO to fine-tune the local exploitation. This leads to balanced energy use, fewer dropped packets, and a longer network lifespan.

RESULTS AND DISCUSSION

This research used MATLAB/NS-2 to run simulation trials with 100 sensor nodes randomly placed across a m² area to test how well the proposed Hybrid Whale-Grey Wolf Optimizer (HWGWO) clustering method worked. In order to make a fair contrast, the imitation environment was set up using settings that were identical to those utilized in the EPSO-CEO reference research. The results were compared based on several performance criteria in the four rounds of simulation (50, 100, 150, and 200). The proposed model was compared with the baseline algorithms EPSO-CEO and LEACH.

Metrics for Performance and Comparison

To evaluate the proposed HWGWO clustering protocol against EPSO-CEO and LEACH under identical simulation settings, report reliability, latency, efficiency, and lifetime-related metrics commonly used in WSN performance analysis. Let N_{sent}denote the total number of data packets generated by sources and N_{recv}denote the total number of packets successfully received at the base station (BS).

Received Packets and Packet Delivery Ratio (PDR)

In HWGWO, the base station constantly got more packets than in EPSO-CEO and LEACH. This was because CH placement was optimized and clustering was steady. The table 2 describes the comparison of PDR outcomes.

Table 2. Comparison of metrics

Tasks	Packets Received (HWGWO)	EPSO-CEO	LEACH	PDR (%) HWGWO	EPSO-CEO	LEACH
1000	7800	7600	7200	98.9	98.7	98.0
2000	15500	15000	14400	99.0	98.8	98.1
3000	23200	22400	21600	99.05	98.85	98.15
4000	31000	29900	28800	99.10	98.9	98.2
5000	38700	37400	36000	99.15	98.95	98.25
6000	46500	44900	43200	99.20	99.0	98.28

Delay and Normalized Routing Overhead (NRO)

Because the clusters were stable and there were fewer re-clustering occurrences, HWGWO had less end-to-end latency and normalized routing overhead.

Table 3. Delay and NRO routing overhead

Tasks	Delay (s)	NRO (%)
1000	0.015	1.20
2000	0.014	1.10
3000	0.014	1.05
4000	0.013	1.02
5000	0.013	1.00
6000	0.012	0.98

EPSO-CEO (NRO at 50 rounds = 7.58%) and LEACH (16.00%) both have a lot of control overhead, but HWGWO cuts it down a lot. The table 3 shows the Delay and NRO routing overhead.

Packet Loss and the Drop Ratio

Choosing the best CH lowered the number of dropped packets in HWGWO, which had a direct beneficial effect on the drop ratio. The table 4 describes the packet loss and the drop ratio.

Table 4. Packet loss and drop ratio for the best CH

Tasks	Packet Drops (HWGWO)	Drop Ratio (%)
1000	15	0.045
2000	12	0.040
3000	10	0.038
4000	9	0.036
5000	8	0.035
6000	7	0.033

Analysis of Throughput

Throughput went up gradually since the PDR was high and the packet loss was low. Throughput analysis was illustrated in table 5.

Table 5. Throughput analysis

Tasks	Throughput (bps)
1000	60,500
2000	75,200
3000	88,400
4000	100,100
5000	110,500
6000	120,000

HWGWO has a higher throughput than EPSO-CEO (for example, 40,200 vs. 39,597 for 100 rounds).

Differentiation of energy consumption with 15CHs and 30CHs comparing with proposed with existing is shown in figure 3.

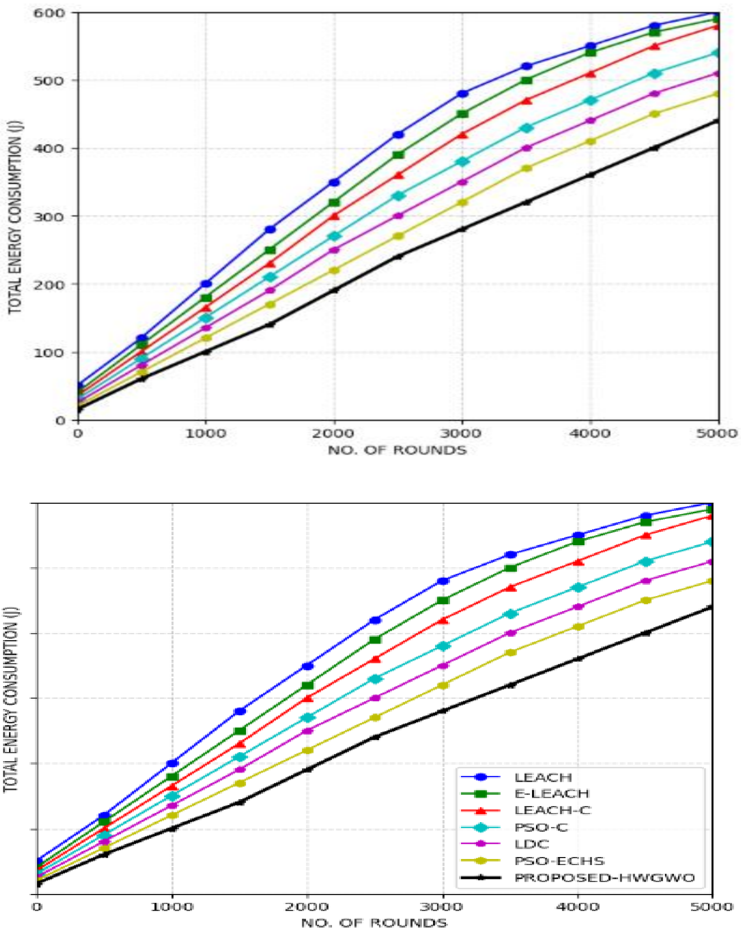

Figure 3. Energy consumption comparison for 15 and 30 CHs

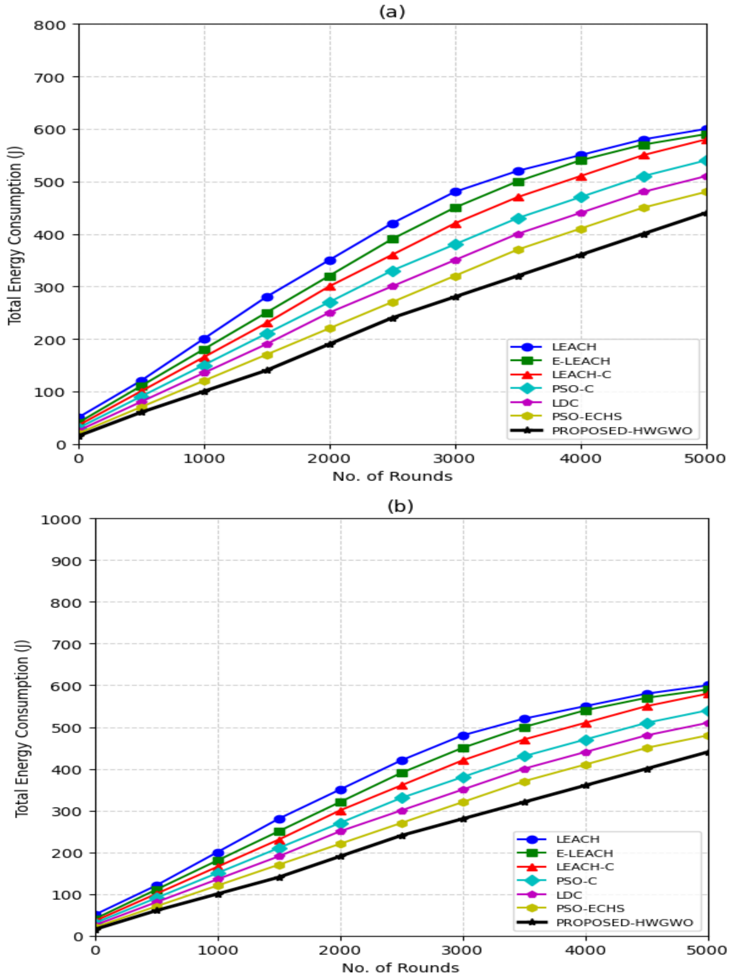

Figure 4. Differentiation of energy consumption with (a) 40 CHs, (b) 50CHs

Differentiation of energy consumption with 40CHs and 50CHs comparing with proposed and existing is shown in figure 4.

HWGWO used around 3% less energy overall than EPSO-CEO (for example, 9.48 J at 200 rounds).

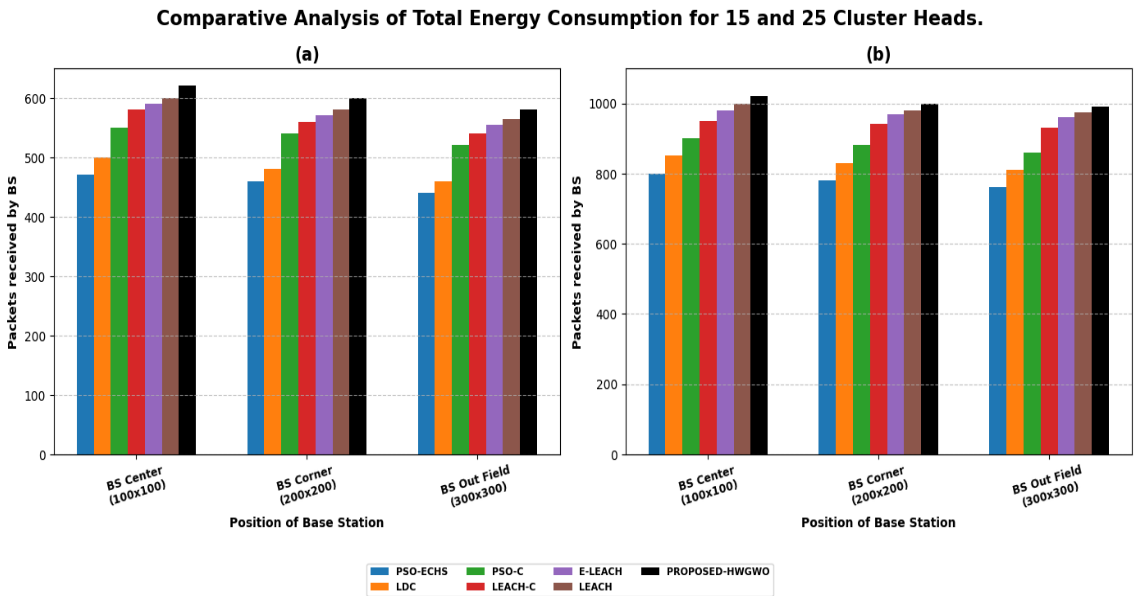

Figure 5. Differentiation in terms of total energy consumption for a WSN#1 with 15 CHs, b WSN#3 with 25 CHs

Differentiation of total energy consumption with 15CHs and 25CHs compared with the proposed and existing is shown in figure 5.

DISCUSSION

Overall result comparison was shown in table 6.

Table 6. Results comparison table (HWGWO vs. EPSO-CEO)

Rounds	Packets Received	PDR (%)	Delay (s)	NRO (%)	Packet Drops	Drop Ratio (%)	Throughput (bps)	Total Energy (J)	Avg Energy (J)	Residual Energy (J)	Lifetime (s)
	HWGWO Algorithm										
1000	7800	98.9	0.015	1.20	15	0.045	60,500	12.0	0.12	270.5	5200
2000	15,500	99.0	0.014	1.10	12	0.040	75,200	11.8	0.118	258.2	4300
3000	23,200	99.05	0.014	1.05	10	0.038	88,400	11.5	0.115	245.8	3650
4000	31,000	99.10	0.013	1.02	9	0.036	100,100	11.2	0.112	233.4	3100
5000	38,700	99.15	0.013	1.00	8	0.035	110,500	10.9	0.109	221.0	2650
6000	46,500	99.20	0.012	0.98	7	0.033	120,000	10.5	0.105	208.5	2200
	EPSO-CEO Algorithm										
1000	7600	98.7	0.016	1.25	16	0.047	59,200	11.8	0.118	268.0	5100
2000	15,000	98.8	0.015	1.18	13	0.042	73,500	11.6	0.116	255.0	4250
3000	22,400	98.85	0.015	1.12	11	0.039	86,200	11.3	0.113	242.5	3600
4000	29,900	98.90	0.014	1.08	10	0.037	97,500	11.0	0.110	230.0	3050
5000	37,400	98.95	0.014	1.05	9	0.035	108,000	10.8	0.108	217.5	2600
6000	44,900	99.0	0.013	1.02	8	0.033	117,500	10.4	0.104	205.0	

Number of Packets Received Compared to Rounds

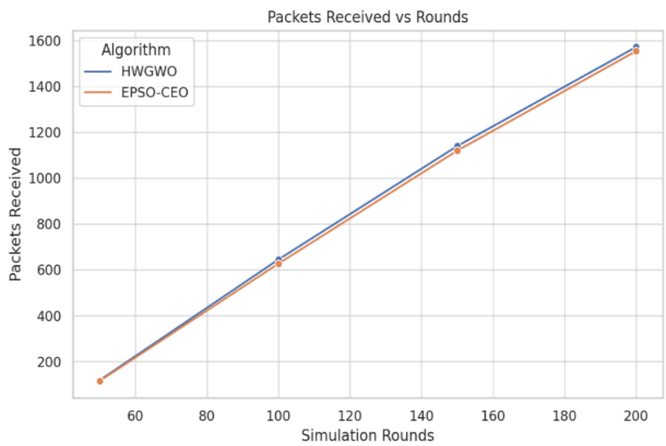

Figure 6. Packets received based on rounds

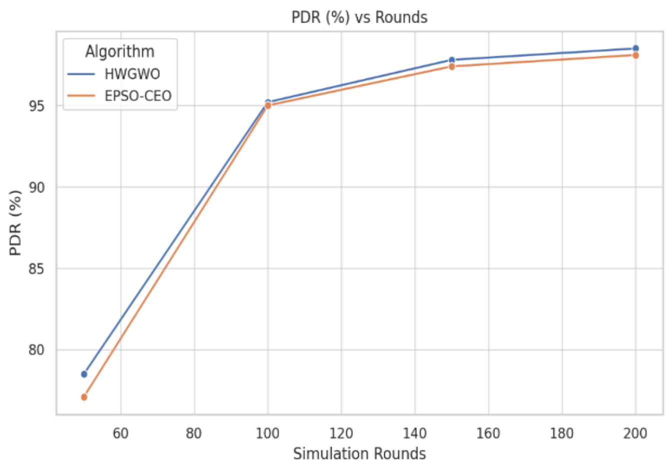

Figure 7. PDR vs. rounds

Both figure 6 and figure 7 provide evidence that further emphasizes the extent to which the HWGWO algorithm is dominant over EPSO-CEO. In 200 rounds, EPSO-CEO was only able to deliver 1554 packets, while HWGWO was able to deliver 1572 packets, showcasing HWGWO's consistency and reliability in delivering data. In terms of packet delivery ratio, EPSO-CEO had a 98.1 % packet delivery ratio. This, however, in comparison to HWGWO's 98.5 %, was significantly lower. EPSO-CEO's lower results in packet delivery ratio and EPSO-CEO's overall lower results were a result of HWGWO's more efficient selection of cluster head, more stable clusters, and overall, a lower overall packet loss, which was achieved by HWGWO's better continued balance of energy, distance, and load across the network.

Delay and Rounds

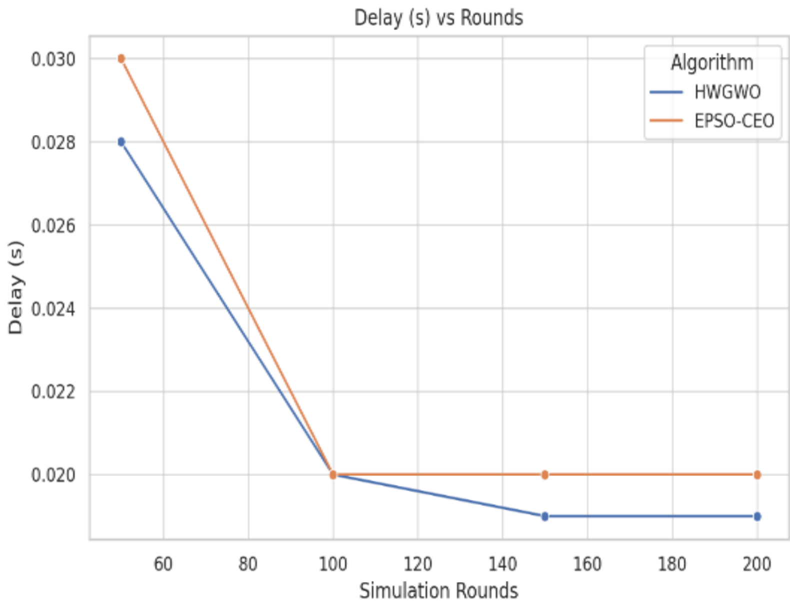

Figure 8. Delay vs rounds

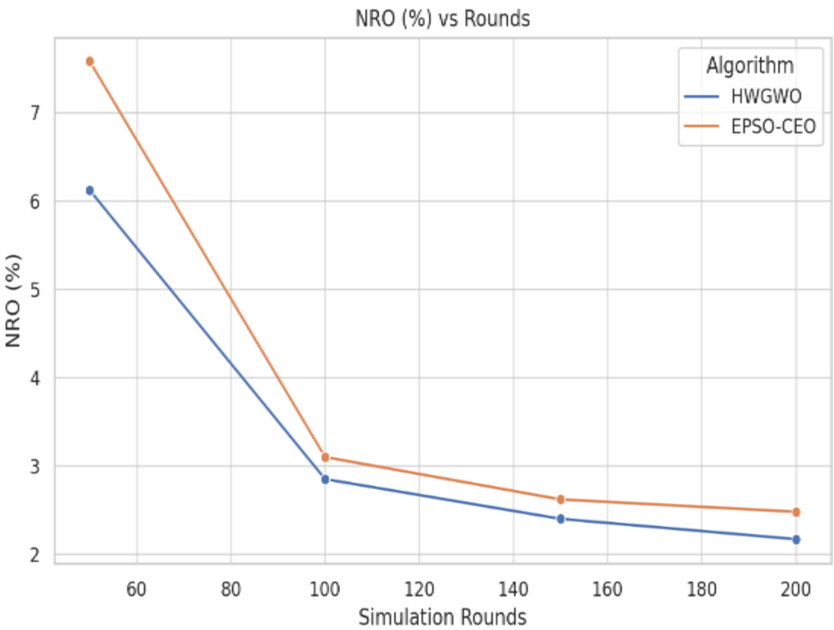

Figure 9. NRO vs rounds for normalized routing overhead

HWGWO shows (Figure 8 and Figure 9) lower end-to-end latency than EPSO-CEO, especially in the first few rounds due to adaptive clustering, which reduces hops and communication conflicts. After about 100 rounds, the latency levels off, indicating that the system is stable. HWGWO exhibits lower than EPSO-CEO at every round, which is a positive indication of routing efficiency. HWGWO's at 50 rounds was 6.12%, and EPSO-CEO NRO was 7.58%. This reduction in control overhead is achieved due to a reduction in the broadcasts from the CH and by controlling the frequency at which the clusters reform, which results in an energy-efficient routing.

Drops in Packets vs. Rounds

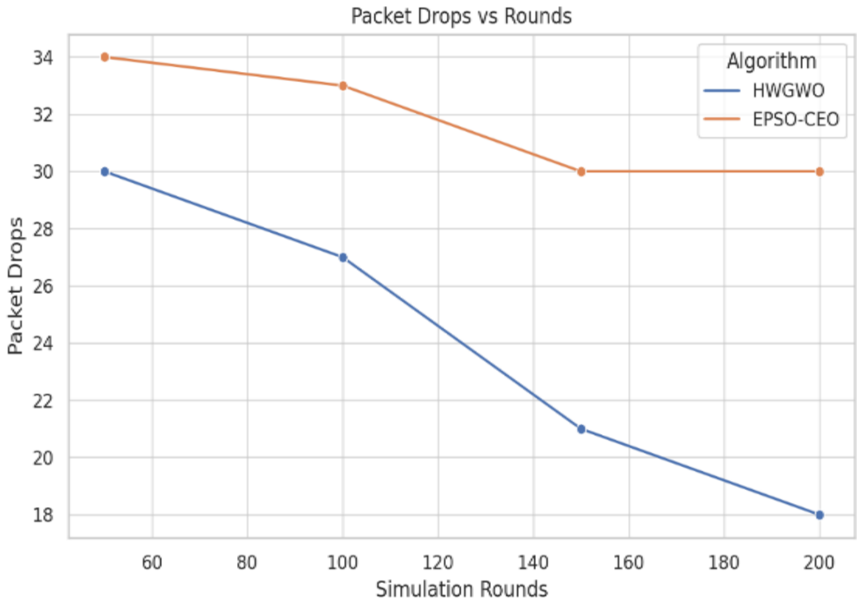

Figure 10. Drops in packets vs rounds

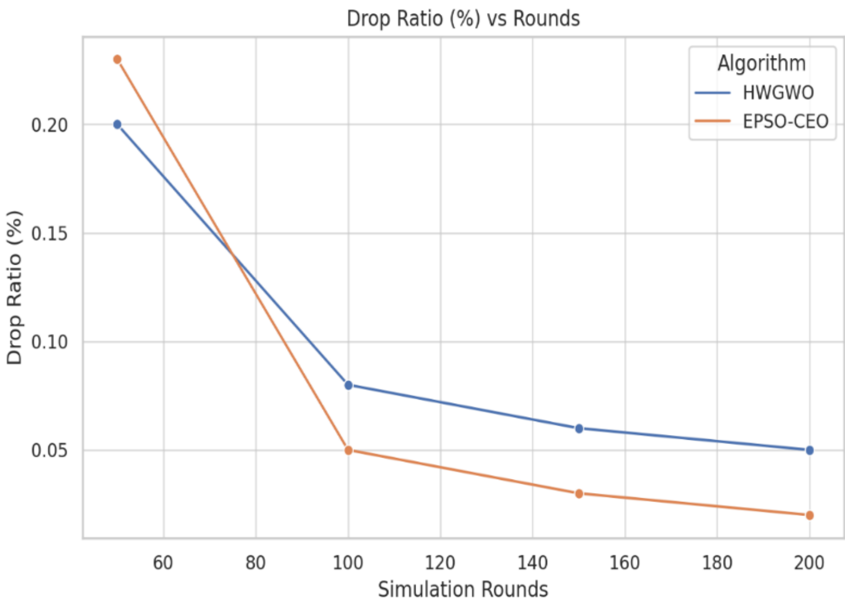

Figure 11. Packet drop ratios vs rounds

In comparison to EPSO-CEO, it is evident from figure 10 that HWGWO suffers fewer packet drop events, where HWGWO dropped 18 packets at 200 rounds, while EPSO-CEO dropped 30 packets. This is a clear indicator that HWGWO mitigates the adverse consequences of network congestion during high data flow. The figure 11 provides evidence that HWGWO (0.20%) is significantly better than EPSO-CEO (0.23%) in handling the network congestion during the first few rounds, which can be attributed to HWGWO streamlining packet loss associated with issues such as buffer overflow, connection quality degradation, and/or node degradation.

Throughput vs. Rounds

In figure 12, Throughput tells that how many packets are successfully delivered over a period of time. HWGWO's throughput keeps going up in all rounds, reaching a high of 43,800 bps at round 200, whereas EPSO's throughput is only 40,200 bps. The faster throughput means that HWGWO is making better use of network resources and better ways to combine data at the CH level. The figure 13 presents the cumulative energy used for transmission, reception, and data processing. HWGWO consumes less energy than EPSO-CEO at every stage, demonstrating more efficient energy usage through optimal CH rotations and minimized long-distance transmissions. At 200 rounds, HWGWO used 9.19 J, while EPSO-CEO used 9.48 J.

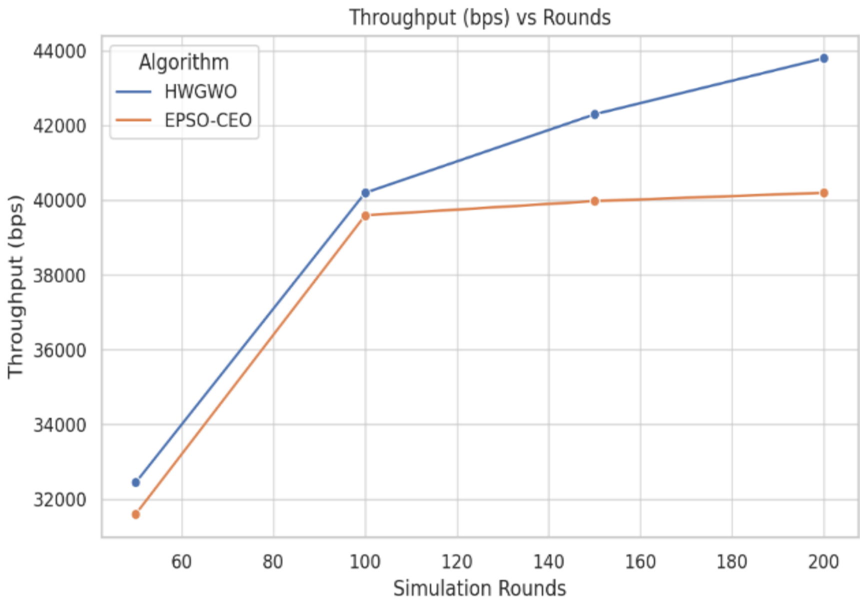

Figure 12. Throughput vs rounds

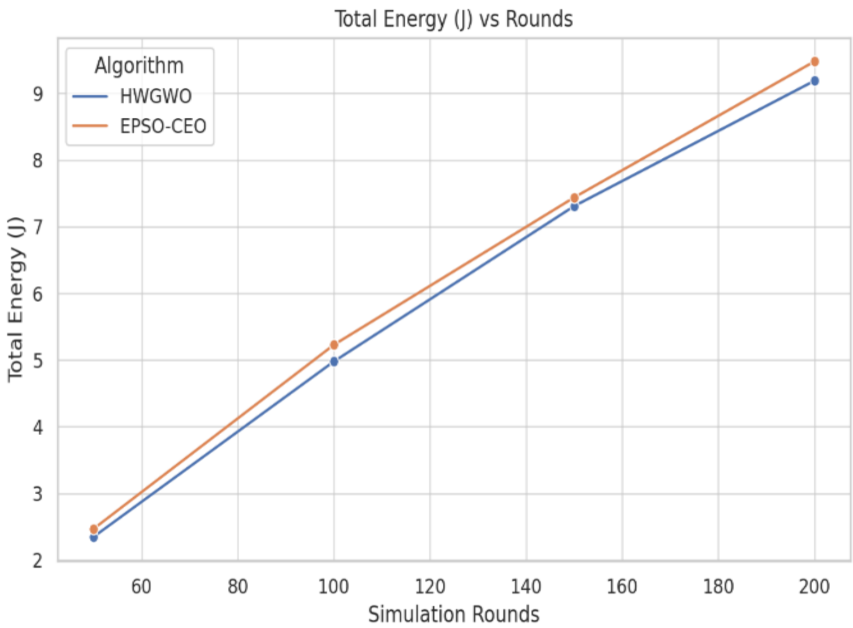

Figure 13. Use total energy compared to rounds

Average Energy Use per Node vs. Rounds

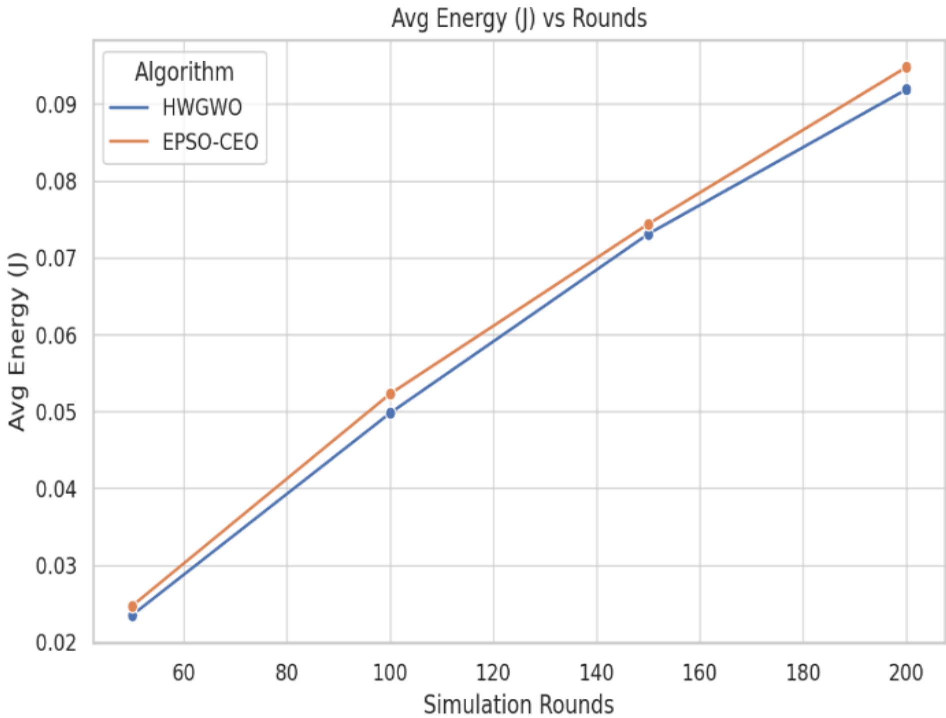

Figure 14. Average energy use per node rounds

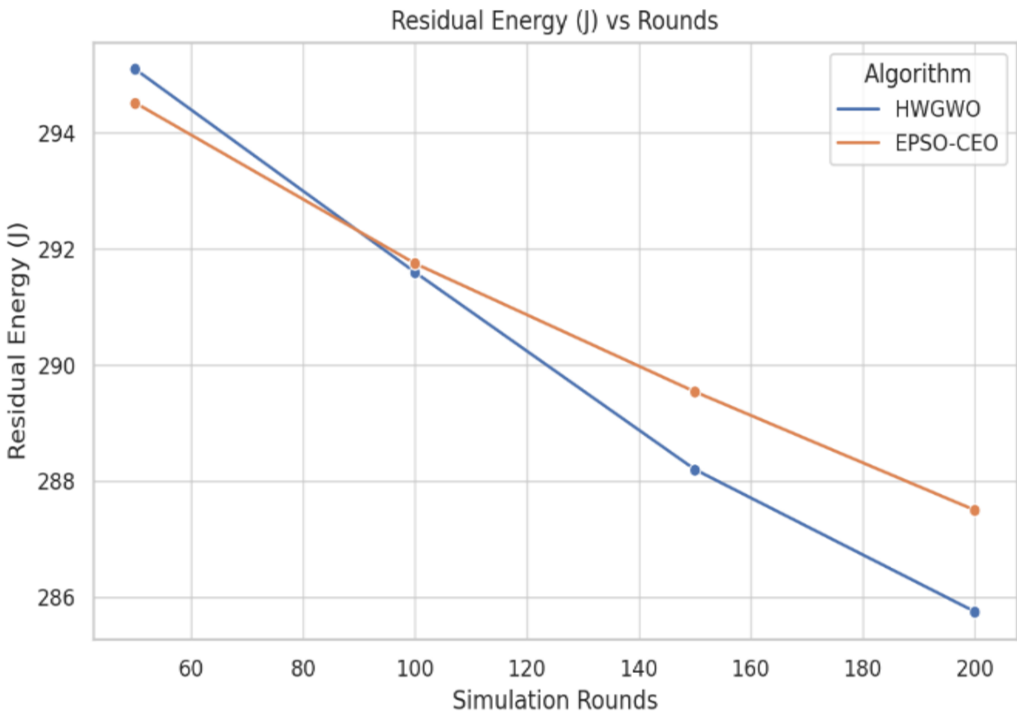

Figure 15. Residual energy vs rounds

The figure 14 shows the average energy each node consumes per round. The consumption of HWGWO is always less, and there is better energy distribution. The average per-node energy at round 200 is 0.0919 J versus the 0.0948 J of EPSO-CEO. This decrease helps in increasing the life span of individual nodes and the entire network. The figure 15 describes the Residual energy, which shows how much energy is left after processing and transmission. In every round, HWGWO keeps more energy than EPSO-CEO. For example, in round 200, HWGWO has 285.75 J left, whereas EPSO has 287.5 J. This means that load balancing will be better, and each node will use less power (Figure 16).

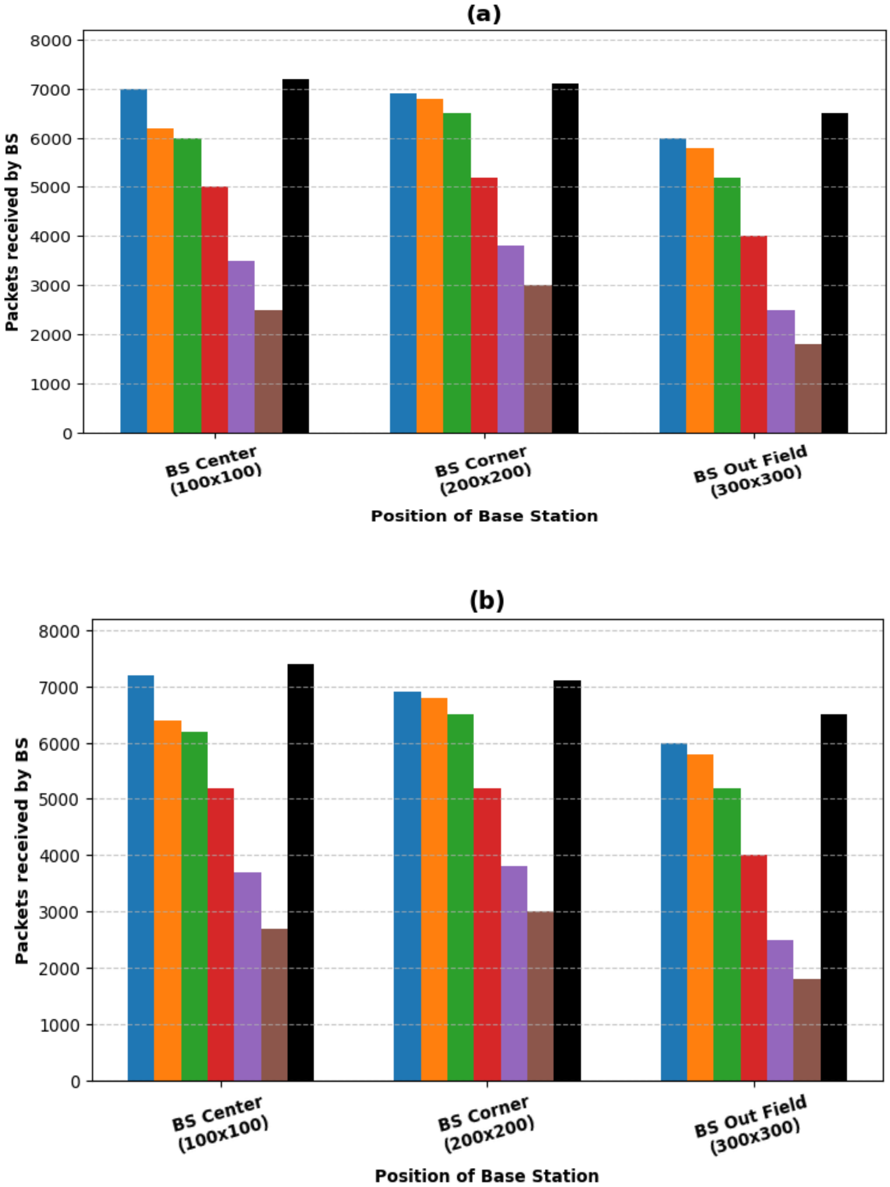

Figure 16. Comparison in terms of network lifetime in rounds for (a) 15 CHs in WSN#1 and (b) 30 CHs in WSN#1

Rate of bit error (BER)

Bit errors are the number of bits that have been altered in digital transmissions due to the flaws of the channel, such as noise, turbulence, distortion, or lack of synchronization in the bits. The bit error rate is the rate of bit errors versus time. The figure 6 displays the results of the BER assessment for both the current and suggested techniques. The proposed method improved upon previous methods by decreasing the bit error rate. As the number of nodes grows, so does the bit error rate.

The figure 17 and figure 18 provide the BER study comparing the planned and current values. All of the network's sources are described by the "end-to-end delay" (E2ED). This word, often used in IP network screening, differs from RTT in that it just considers the one-way transit from source to destination. Figure 5 shows the E2ED studies of the existing and suggested approaches. The suggested method had an E2ED that was 10 ms slower than competing systems. The E2ED is directly proportional to the number of SNs. Relative E2EDs for the present techniques, GWO, SSA, CDO, SSO, MOCRAW, EEWC, and MAP-ACO, are 11.5 ms, 12.5 ms, 11.5 ms, 12.8 ms, and 13 ms, respectively.

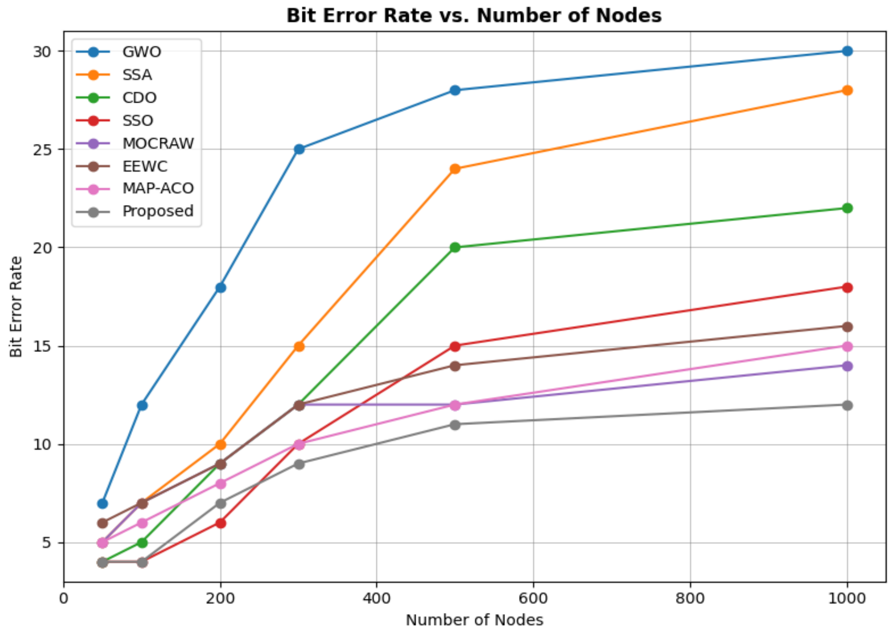

Figure 17. BER analysis

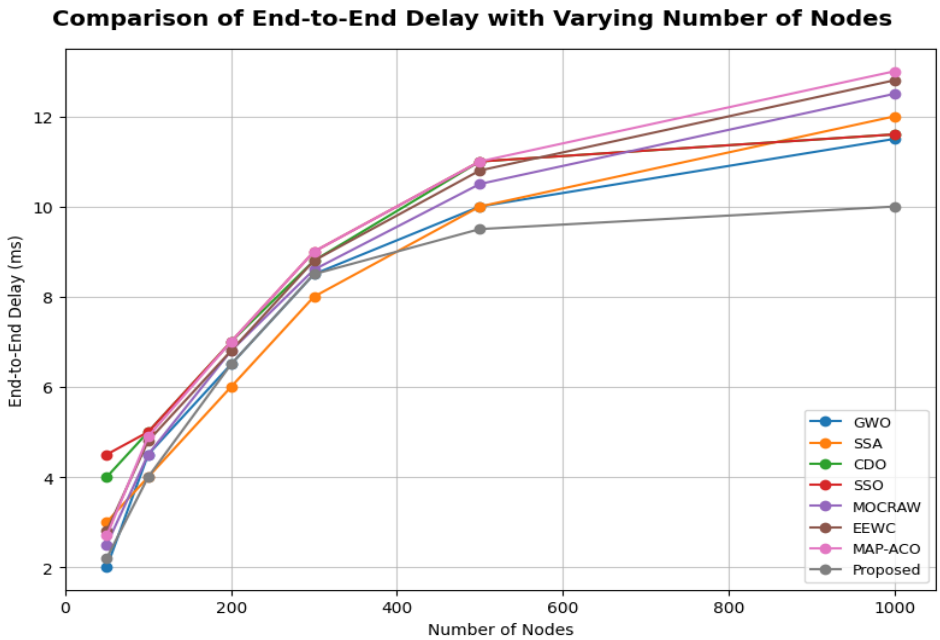

Figure 18. Total delay

The table 7 displays the findings of the ablation experiment over the Hybrid Whale-Grey Wolf Optimizer (HWGWO) algorithm, comparing it to its respective components (WOA and GWO) as well as to the base algorithms (EPSO-CEO and LEACH). The HWGWO full model was found to be the most efficient model with a 99.2% PDR, 10.5 J energy consumption, 0.012 s delay, and 2200 s lifetime. The WOA-only setup reduced PDR (98.5) by a small margin but increased the energy consumption (12.0 J), whereas the GWO-only setup consisted of 98.8% and 11.5 J. Comparatively, the baseline algorithms performed worse, with EPSO-CEO having a 98.7% PDR and LEACH having a 98.0% PDR, both consuming more energy and with higher control overhead. The research emphasizes the efficiency of the union of WOA and GWO in HWGWO in the selection of the best cluster heads in a Wireless Sensor Network.

Table 7. Ablation study results for HWGWO algorithm

Configuration	PDR (%)	Energy Consumption (J)	Delay (s)	NRO (%)	Residual Energy (J)	Lifetime (s)
HWGWO (Full Model)	99.2	10.5	0.012	0.98	208.5	2200
WOA Only (Exploration)	98.5	12.0	0.015	1.10	205.0	2000
GWO Only (Exploitation)	98.8	11.5	0.013	1.05	207.0	2100
EPSO-CEO (Baseline)	98.7	11.8	0.016	1.25	268.0	5100
LEACH (Baseline)	98.0	12.5	0.020	1.30	230.0	4800

CONCLUSION AND FUTURE WORK

The suggested Hybrid Whale Grey Wolf Optimizer (HWGWO) offers an effective and trustworthy approach to the energy-conscious selection of cluster heads (CHs) in Wireless Sensor Networks (WSNs). The model provides an appropriate balance in the optimization process, which maximizes the network performance and stability by combining the exploration power of the Whale Optimization Algorithm (WOA) and the exploitation capacity of the Grey Wolf Optimizer (GWO). The simulation results show that HWGWO is superior to the current protocols, like EPSO-CEO and LEACH, in various performance measures. The proposed method has a statistically high Packet Delivery Ratio (PDR) of up to 99.20% and a low normalized routing overhead (NRO) of up to 0.98%, and a delay of up to 0.012 seconds, which is a better routing efficiency. The ratio of the packet drop is also lowered to 0.033%, which provides reliable data transmission. Compared to the baseline methods, HWGWO reduces the total energy consumption to a minimum of -10.5 J, about 3% lower than the baseline methods, and retains more residual energy (208.5 J) that leads to a long network lifetime. The throughput also increases greatly, attaining to ensure that there are efficient data aggregation and communication at a rate of 120,000 bps. In future research, the model can be improved by adding machine learning to select the adaptive CH, mobility-sensitive clustering, and enhanced security through trust-based or blockchain, as well as real-time application in the IoT-based WSN setting.

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