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Simulation-based cluster head selection using multi-objective particle swarm optimization for IoT: Trade-off between intra-cluster distance and energy efficiency

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ABSTRACT

Internet of Things (IoT) has transformed modern life by enabling interconnected systems through distributed sensor nodes that collect data from remote locations such as agriculture, wildlife monitoring, and forestry. However, challenges arise due to the limited battery capacity of sensor nodes, affecting network lifetime and energy efficiency. To improve energy conservation and extend network longevity, clustering techniques play a vital role. Although various clustering protocols have been proposed, many still face the "energy-hole" problem caused by inefficient Cluster Head (CH) selection methods. CHs are responsible for managing intra-cluster communication and tend to exhaust energy rapidly, especially those near the base station due to excessive relay traffic. To address this, a Multi-Objective Particle Swarm Optimization (MOPSO) technique is proposed for CH selection to ensure better energy efficiency and intra-cluster distance in IoT-based wireless sensor networks (WSNs). This technique operates in two phases: cluster formation and CH selection. Euclidean distance is used for clustering member nodes, and high-energy nodes are adaptively chosen as CHs using the MOPSO method. Simulations conducted in MATLAB R2019a validate that the proposed MOPSO outperforms existing algorithms such as LEACH, LEACH-FL, LEACH-FC, KM-PSO, EECHS-ARO, HSWO, and EECHIGWO by mitigating premature convergence and enhancing CH selection accuracy. The proposed technique achieves improvements of 10.02% in packet delivery rate and 9.68% in network lifetime. Results indicate that 105 nodes remain active after the final simulation round, with lower average energy consumption of 0.0570 Joules.

Contribution/Originality: This study contributes to the existing literature by examining the problem and exploring a novel clustering protocol for improved network lifetime, average energy consumption, reduced data redundancy, and increased number of alive nodes. It offers new insights into distance-aware and energy-efficient clustering, enhancing the reliability and efficiency of network operations.

1. INTRODUCTION

The *IoT* has introduced a transformational hypothesis in contemporary technical studies, influencing both academia and industry. *IoT* has evolved since its invention by Ashton [1] as a universal network of interrelated physical devices based on sensing, processing, and communication capabilities [2-4]. These appliances enable effortless data acquisition and intelligent communication in various functions, such as healthcare, precision agriculture, industrial automation, smart homes, transport, and monitoring systems. Owing to real-time data processing and worldwide connectivity, *IoT* enhances operational efficiency, decision-making accuracy, and user experience across multiple fields [5-7].

The basic investment in *IoT* systems, i.e., Wireless Sensor Networks, includes scattered sensor nodes that monitor the environment and transmit collected information to the base station for analysis. Advances in microelectronics and low-power strategies have enabled the deployment of small, energy-efficient sensors in dynamic and complex settings [8]. Despite these technological advances, sensor nodes remain limited by small computation, memory, and non-rechargeable batteries. Consequently, energy reduction directly affects network lifetime and stability, making energy-efficient processes a key challenge in *WSN*-based *IoT* architectures [9-11].

Among various approaches for energy conservation, clustering has been recognized as one of the most operational approaches for enhancing energy efficiency and scalability in *WSNs*. In the clustering process, sensor nodes, which are also member nodes, are grouped into different clusters, either of the same size or different sizes, associated with a particular Cluster Head. These *CHs* are entirely responsible for the accumulation and transmission of data to the required Base Station [12]. Optimal *CH* selection reduces surplus data transmission and balances the network's overall energy usage [13-15]. Several clustering optimization algorithms have been established, including "Particle Swarm Optimization (*PSO*)", "Golden Jackal Optimization (*GJO*)", "Artificial Bee Colony (*ABC*)", "Marine Predator Optimization (*MPO*)", "Coati Optimization Algorithm (*COA*)" and "Whale Optimization Algorithm (*WOA*)". However, most of these techniques suffer from slow convergence rates and inefficient energy utilization [8], which leads to impulsive node failures as well as reduced network longevity [16-18].

To overcome these restrictions, this work proposes a clustering technique called "Multi-Objective Particle Swarm Optimization" for energy efficiency and optimized *CH* selection in the environment of IoT-enabled *WSNs*. The suggested method is based on a clustering approach developed from the parameters of inter-node distance (Fitness function f_1) and dynamically chooses *CHs* based on remaining energy and positional characteristics (Fitness function f_2). This algorithm demonstrates quicker convergence in the diagnosis of *CH* replacement, thereby lowering computational complexity and power usage. Many detailed simulations were conducted in *MATLAB 2019a*. This article ensures that the proposed solution surpasses benchmark algorithms like *EECHS-ARO*, *HSWO*, and *EECHIGWO* in terms of the number of alive nodes, packet delivery ratio, and energy efficiency. The simulation results prove the robustness and flexibility of the *MOPSO*-based strategy for large-scale *IoT* settings.

The paper outline will be as follows: Section II will contain the comprehensive evaluation of the existing methods of Cluster Head (*CH*) selection through the diversity of optimization algorithms. Section III presents the problem statement and identifies the main challenges associated with the issue of energy-efficient *CH* selection in *IoT*. Section IV proposes a new method of the best *CH* selection and cluster creation, called Multi-Objective Particle Swarm Optimization (*MOPSO*). Section V addresses the setup of the simulation, the evaluation of the performance, and the proportional analysis of the existing algorithms and the suggested technique. Finally, Section VI ends the suggested work and indicates what directions to follow in the future.

2. LITERATURE REVIEW

In the WSN, clustering has received significant attention to ensure longer network life and energy efficiency. The groundbreaking clustering method was called *LEACH* (Low-Energy Adaptive Clustering Hierarchy), which balanced energy usage by organizing nodes into clusters in a probable way [19]. It has been improved later and the performance of LEACH has been boosted, though its fundamental principles are still relevant [15]. Fuzzy logic has been effectively applied to various phases of clustering that include *CH* selection, finding cluster radius, node association, identification of next-hop *CH*, and re-clustering [20]. Routing techniques were integrated with clustering to decide optimal next-hop *CHs* [16] that enables hybrid protocols to function as both clustering and routing mechanisms [17]. The *LEACH-FL* mechanism employs a fuzzy inference method for *CH* selection [21, 22]. Each node evaluates three parameters corresponding to residual energy, local node compactness, and proximity to the Base Station by considering a fuzzy probability. "Center of Area (*COA*)" de-fuzzification method generates hard probability value, which is used to compare with *LEACH's* random threshold value. Nodes that exceed the threshold value are elected as *CHs*, while other nodes remain as regular members. Cluster formation and *TDMA-based* data transmission follow traditional *LEACH* procedures [23-25].

LEACH-FC improves the energy efficiency by allocating the load across each node [26-28]. A Mamdani fuzzy system was applied to calculate *CH* probabilities based on energy, concentration, and significance, while a secondary fuzzy system introduced for non-*CH* nodes in selecting suitable *CHs*.

Similarly, *KM-PSO* combines both the K-means clustering method with PSO technique to enhance cluster centers, while fuzzy logic decides primary and secondary *CHs* [29]. *LEACH-SF* relates fuzzy c-means clustering methods in heterogeneous networks, enhancing node-2-centroid distances and uses artificial bee colony algorithms to enhance fuzzy rules for *CH* selection [25, 30, 31]. Selecting an ideal set of *CHs* is a problem that comes under *NP*-hard due to the large number of potential clustering patterns [27]. Swarm intelligence algorithms, mainly *PSO*, have proven efficient for almost optimal *CH* selection within rational computation times [32, 33]. Hybrid approaches were proposed by combining *PSO* with fuzzy logic [34, 35], sink mobility [36], and harmony search algorithms (*HSA*) [37] that further improved network lifetime and energy efficiency. These works concentrate on the current state of development of *CH* selection procedures and emphasize the necessity of high-speed converging, power-conscious optimization schemes within IoT-enabled *WSNs*.

EECHS-ARO is a groundbreaking protocol that chooses CHs in the best way possible based on a nature-inspired computation algorithm known as Artificial Rabbit Optimization (ARO) [38-40]. This *ARO* approach helps in the proactive choice of *CHs* by taking into account parameters that involve distance to the *BS* and residual energy, and the objective of being able to balance the energy usage and network lifespan.

HSWO employs both hybrid optimization methods, Sailfish Optimization Algorithms (*SFO*) and Whale Optimization Algorithms (*WOA*) [41]. This protocol exploits the nature of approaches to effectively select *CHs* and optimize data routing paths, thereby guaranteeing efficiency in both data transfer and gathering, besides increasing longevity and network performance. *EECHIGWO* addresses the issue faced in selecting the *CH* by using an upgraded version of the "Grey Wolf Optimization (*GWO*)" technique [42]. *GWO* is a reliable optimization technique, and its enhanced variant, *EECHIGWO*, is intended to deliver a robust solution for assembling optimal clusters and selection of appropriate *CHs*, resulting in network longevity and better energy management than basic *LEACH* and possibly outperforming other metaheuristic-based methods [43-45].

Contemporary metaheuristic algorithms (*KM-PSO*, *EECHS-ARO*, *HSWO*, *EECHIGWO*) [46-48] typically exhibit enhanced efficacy compared to conventional methods like LEACH and its simpler variants (*LEACH-FL*, *LEACH-FC*) with respect to reliability, data throughput and network lifetime because they use advanced and global optimization techniques for routing and clustering decisions.

Taking into consideration the limitations of existing techniques, an optimized methodology has been proposed in our work by considering four parameters: the number of alive nodes at the end of iterations (maximum), average energy consumption (minimum), packet delivery ratio (maximum), and communication overhead (minimum) to ensure overall system performance.

3. PROBLEM STATEMENT

Energy is a part of significant resource in *IoT*-based *WSN* networks, and its effective management directly influences network lifetime [9]. This work concentrates on minimizing energy utilization by optimizing *CH* selection through clustering, thereby extending the network longevity. In the proposed *MOPSO* algorithm, clustering is implemented in two successive steps: *CH* selection followed by cluster formation.

The selection of *CH* processes introduces a multi-parameter fitness function to recognize optimal *CHs*. The key parameters are:

1. Relative Distance between *CHs* and Member Nodes (*MNs*)

   The average Euclidean distance between each *CH* (CH_m) and all *MNs* (MN_i) is computed as:

$$\frac{1}{m}\sum_{i=1}^{n} Euclidean\_distance(MN_i, CH_m) \qquad (1)$$

Where n represents number of Member Nodes and m represent number of Cluster Heads. Selecting CHs nearer to MNs reduces energy consumption during intra-cluster communication.

2. Relative Distance between Base Station (*BS*) and *CHs*

The relative distance from each CH to the Base Station is calculated as:

$$\frac{1}{m} Euclidean\_distance(CH_m, BS) \qquad (2)$$

Minimizing this distance moderates the energy consumed during the data transmission from *CHs* to the *BS*.

The above two distance metrics represented in Equations 1 and 2 are combined into a single objective function ($f_{distance}$) as:

$$Min\ (f_{distance}) = \sum_{j=1}^{m} \frac{1}{m} \left(\sum_{i=1}^{n} Euclidean\_distance(MN_i - CH_j) + Euclidean\_distance(CH_j, BS)\right) \qquad (3)$$

3. Overall Energy of Cluster Heads

Residual energy of the selected *CHs* is taken into consideration to guarantee the most effective *CH* is chosen for the entire network. The main aim is to maximize the sum of *CH* energies (f_{energy}), or to minimize its inverse:

$$Min\ (f_{energy}) = \frac{1}{\sum_{j=1}^{m}(e(CH_j))} \qquad (4)$$

Where $e(CH_j)$ denotes the residual energy of CH_j.

The above three objectives are combined to calculate total fitness function ($f_{fitness}$) to ensure optimal Cluster Head selection.

$$Min\ (f_{fitness}) = (\alpha * f_{distance}) + ((1-\alpha) * f_{energy}) \qquad (5)$$

$$0 < \alpha < 1 \quad \text{and} \quad 0 < (f_{distance}, f_{energy}) < 1$$

Where α is a weight factor for fine-tuning. Minimizing fitness ensures the selection of *CHs* that optimize both energy efficiency and network coverage.

4. PROPOSED OPTIMIZATION ALGORITHM AND SYSTEM MODEL

4.1. Network Model

In the proposed clustering-based algorithm "Multi-Objective Particle Swarm Optimization (*MOPSO*)", the wireless sensor networks consist of sensor nodes representing as $n = \{n_1, n_2, n_3, \ldots, n_k\}$ that are randomly spread within the identifying field of (*300 m X 400 m*) frame. Each node is assigned the role of either a *CM*-Cluster Member or a *CH*-Cluster Head.

During the data collection phase, *CMs* sense actual factors and communicate the collected information to their respective *CHs* via single-hop communication. The *CHs* perform data aggregation to reduce redundancy and then forward the data to the *BS* or, in some cases, to the sink node.

The cluster head selection procedure is carried out using the *MOPSO* approach, which varies on several competing criteria, such as maximizing residual energy for selected *CHs* and minimizing intra-cluster communication distance. Once optimal *CHs* are identified, clusters are formed based on spatial proximity and energy limitations of the adjacent nodes.

The *BS* then implements data analysis and network management functions like fitness functions, using the accumulated *CH* information. The overall network design is illustrated in Figure 1.

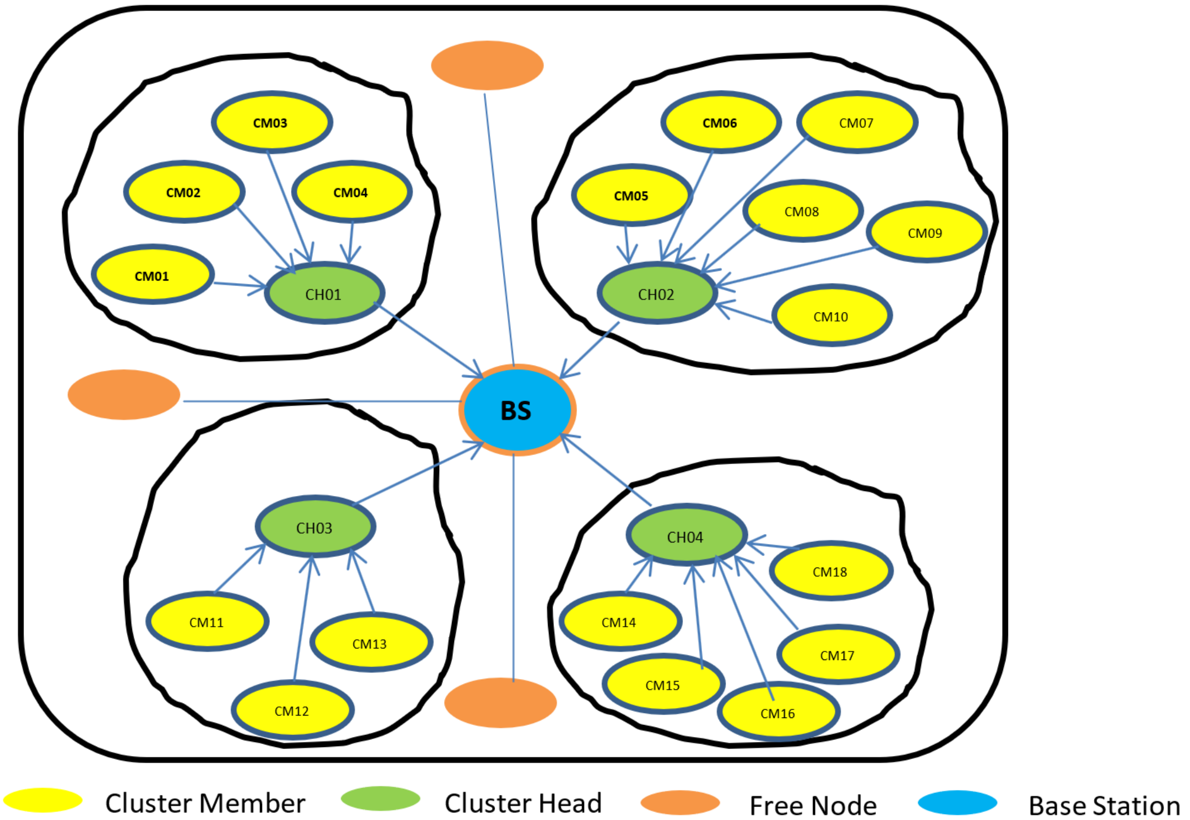

Figure 1. Network model illustrating the Multi-Objective Particle Swarm Optimization (*MOPSO*) based *CH* selection and formation of cluster process in a wireless sensor network.

The proposed *MOPSO-based* network model is developed under the following assumptions.

a) Within the monitoring region, sensor nodes are randomly dispersed.

b) Every node holds a unique identifier to enable distinct recognition within the network.

c) All sensor nodes are uniform with respect to initial energy and computational ability.

d) The *BS* is sited at the geometric center of (*145 m X 255 m*) of the sensing field.

e) Each node has prior information about the base station's location.

f) The base station receives accumulated data packets communicated by the Cluster Heads (*CHs*) from their respective Cluster Members (*CMs*).

This communication strategy is illustrated diagrammatically as described in Figure 2.

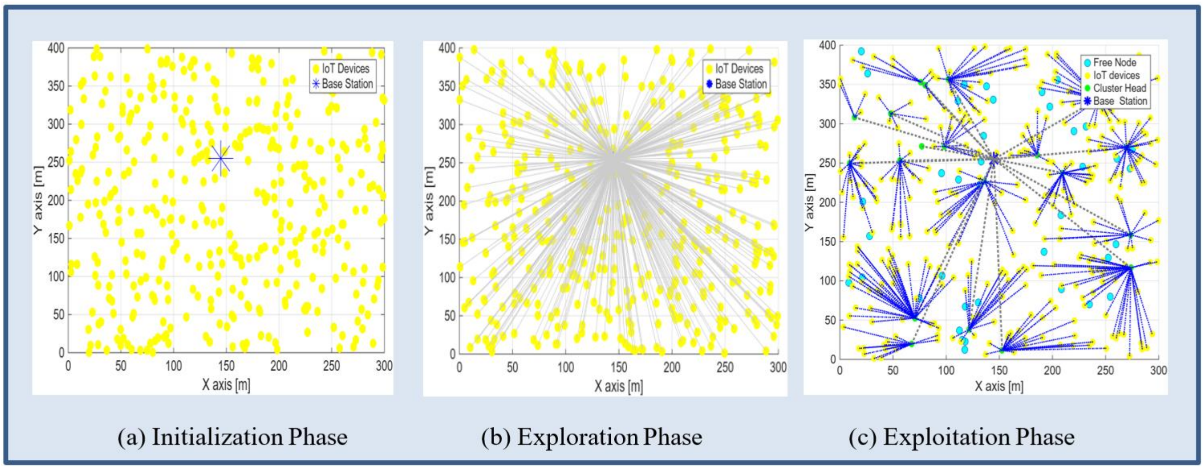

Figure 2. Communication Strategies: (a) Sensor node deployment, (b) Base station control signaling, (c) *CH* selection.

4.2. Energy Model

Due to the sensor nodes' limited power, energy depletion presents a significant challenge in wireless sensor networks. The suggested *MOPSO*-based protocol uses a simplified energy model that accounts for both the multi-path and free-space transmission effects for data in order to overcome this difficulty.

In the proposed model, the energy needed (E_T) to disseminate an n-bit data packet from Node P to Node Q over distance Z is calculated using Equation 6.

$$E_T(n, Z) = nE_{elec} + n\varepsilon Z(P,Q)^{\alpha} = \begin{cases} nE_{elec} + n\varepsilon Z(P,Q)^2 \text{ where } Z(P,Q) < z_0 \\ nE_{elec} + n\varepsilon Z(P,Q)^4 \text{ where } Z(P,Q) \geq z_0 \end{cases} \quad (6)$$

Where E_{elec} is the energy that is used by the transmitter or the receiver circuitry to process 1-bit of data, z_o represents the threshold distance, ε represents coefficients of amplifier energies. The corresponding energy model adopted in the *MOPSO* framework is illustrated in Figure 3. This design forms the basis for optimizing Cluster Head selection to boost both network lifetime and energy efficiency [27].

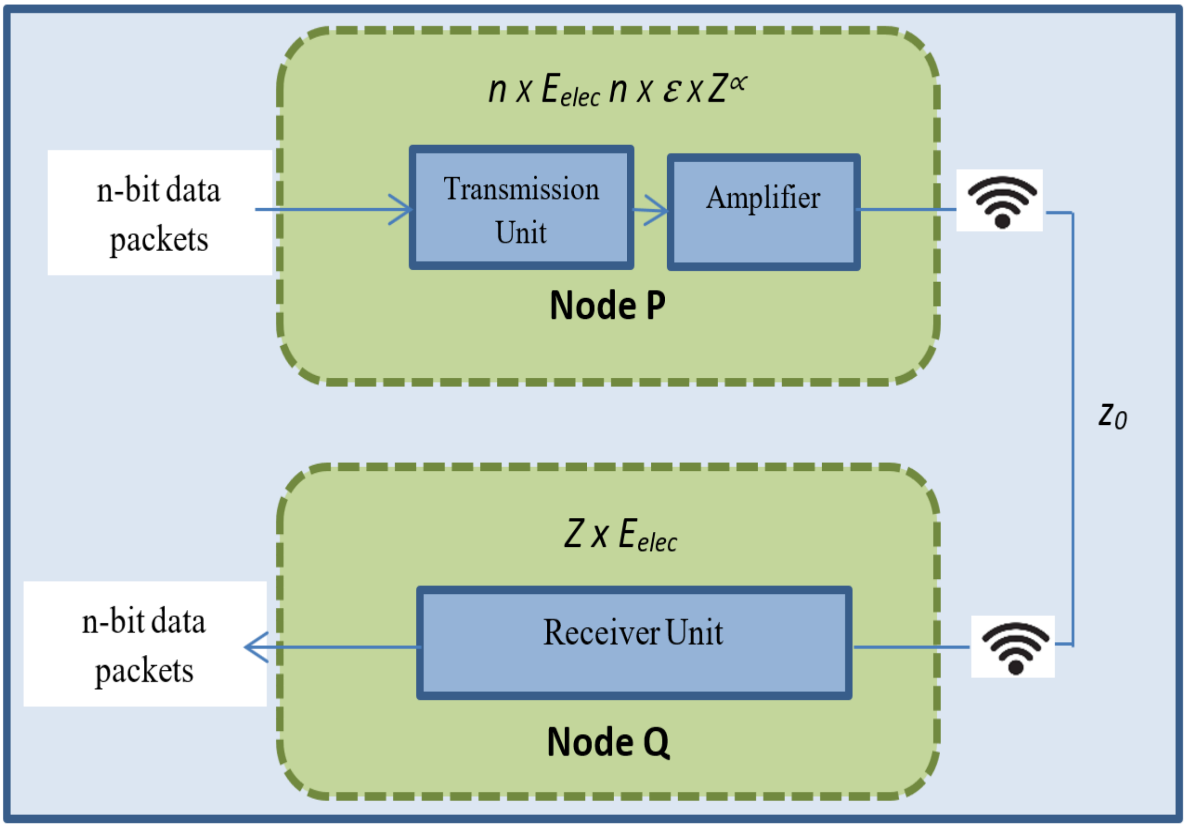

Figure 3. Energy consumption model adopted in the proposed *MOPSO-based* clustering framework.

When the distance Z between Nodes P and Q is less than the threshold distance z_o, the free space ($\mathcal{E}_{fs}$) propagation model is employed to estimate the transmission energy. On the contrary, when $Z \geq z_o$, the multi-path ($\mathcal{E}_{mp}$) diminishing model is applied. The threshold distance z_o serves as the boundary parameter differentiating these two propagation systems and is computed using Equation 7.

$$z_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (7)$$

Furthermore, the amount of transmission energy node P utilizes to transmit an n-bit data packet to the destination Node Q can be determined using Equation 8 as follows.

$$E_T(Z) = ZE_{elec} \quad (8)$$

4.3. Proposed Optimization Algorithm

This article proposes a "Multi-Objective Particle Swarm Optimization (*MOPSO*)" algorithm for efficient cluster head (*CH*) selection in *WSNs* based *IoT*, designed for enhancing network longevity and reducing energy consumption. The proposed algorithm operates in two different phases. In the first phase, optimal *CHs* are nominated using the *MOPSO-based* optimization method that balances multiple performance parameters. In the later phase, different clusters are formed by associating sensing member nodes with their respective *CHs* based on the Euclidean distance principle.

This two-phase mechanism effectively enhances the overall network performance with regards to energy efficiency, latency, and stability. The nomenclature of parameters and symbols employed in the proposed *MOPSO* algorithm is outlined in Table 1.

Table 1. Nomenclature of proposed *MOPSO* algorithm.

Notation	Definition
n	Number of member nodes
R	Iteration count
k	Number of cluster heads
f_1	Fitness function (intra-cluster distance)
f_2	Fitness function (energy efficiency or inter-cluster separation)
$v_i(R)$	Velocity of member node i during iteration R
$x_i(R)$	Current position of member node i
$pbest_i$	Best position by member node i (personal best)
gbest	Best global position found by all particles
w	Weight of inertia
c_1, c_2	Cognitive & social acceleration coefficient
r_1, r_2	Random numbers in the range [0, 1]

The clustering process seeks to satisfy two conflicting objectives.

Maximize intra-cluster similarity (Compactness): Nodes within the same cluster should be closely located to minimize intra-cluster communication costs.

Minimize inter-cluster similarity (Separation): Cluster heads should be spatially well separated to ensure balanced energy consumption and coverage.

To achieve an optimal trade-off between these two goals, a *MOPSO* algorithm is projected. In *MOPSO*, each particle has a potential clustering solution, and the swarm collectively explores the search space to identify a number of efficient, optimal solutions. The optimization process simultaneously evaluates multiple fitness functions that reflect conflicting design goals, such as.

1. Intra-cluster distance minimization (compactness metric)

$$f_1 = E\_dis(CM_i, CH_j) = \sqrt{\sum_{j=1}^{k}\sum_{i=1}^{n}(CH_j - CM_i)^2} \quad (9)$$

Where f_1 denotes fitness function for distance, $E\_dis(CM_i, CH_j)$ denotes the Euclidean distance between member node CM_i and its associated cluster head CH_j.

2. Energy consumption minimization (Separation metric)

$$f_2 = RES\_E(CM_i, CH_j) = \frac{Energy_{avail}}{Energy_{initial}} \quad (10)$$

Where f_2 denotes fitness function for residual energy, $RES\_E(CM_i, CH_j)$ represents the residual energy after the *CH* utilizes it for data transmission and aggregation and the residual energy that is left after the communication of data by the member nodes, $Energy_{avail}$ represents remaining energy and $Energy_{initial}$ represents original energy.

Algorithm: MOPSO-based Cluster Head Selection Algorithm.

Input: Population size of network - *n* nodes

Iterations count - *R*

Number of cluster heads to be elected *k*

Fitness functions: f_1 (intra-cluster distance),

f_2 (energy efficiency or inter-cluster separation)

Output: Optimal positions of particles acting as Cluster Heads

Begin

// Initialization Phase:

1. Initialize populations of particles and represent sets of *CH*(*k*) positions randomly in the network using Equations 1 and 2.
2. Evaluate the multi-objective fitness functions f_1 and f_2 (compactness and separation) for each particle using Equations 3 and 4.
3. Initialize an external archive to accumulate non-dominated Pareto-optimal solutions.
4. For iteration *i*=0 to (*R*-1) do:
5. For each sensor node *j*=0 to (*n*-1) do:

// Exploration Phase:

6. Select a global leader (from the Pareto archive) for the current particle using a selection strategy (Euclidean distance).
7. Update the velocity of the particle using *PSO* rules as below:

$$v_i(R+1) = w.v_i(R) + c_1.r_1.[pbest_i - x_i(R)] + c_2.r_2.[gbest - x_i(R)]$$

8. Update particle position using PSO rules as below:

$$x_i\,(R+1) = \ x_i(R) + v_i(R+1)$$

9. Ensure particle positions are within boundaries of network area, clip if required.

// Exploitation Phase:

10. Optionally, mutate the particle for diversity and fine-tuning.
11. Recalculate multi-objective fitness values f_1 and f_2 for updated position using Equations 9 and 10.
12. Update the particle's personal best if the new position dominates the previous best.
13. Update Pareto archive with non-dominated solutions, apply truncation if archive is full.
14. If a particle achieves optimal *CH* criteria, i.e., best trade-off between energy and compactness, then
15. Select that particle as the best *CH* candidate.
16. Else
17. Continue to subsequent iteration.
18. Terminate for
19. Terminate for
20. Returns best Pareto set of *CH*(*k*).

End

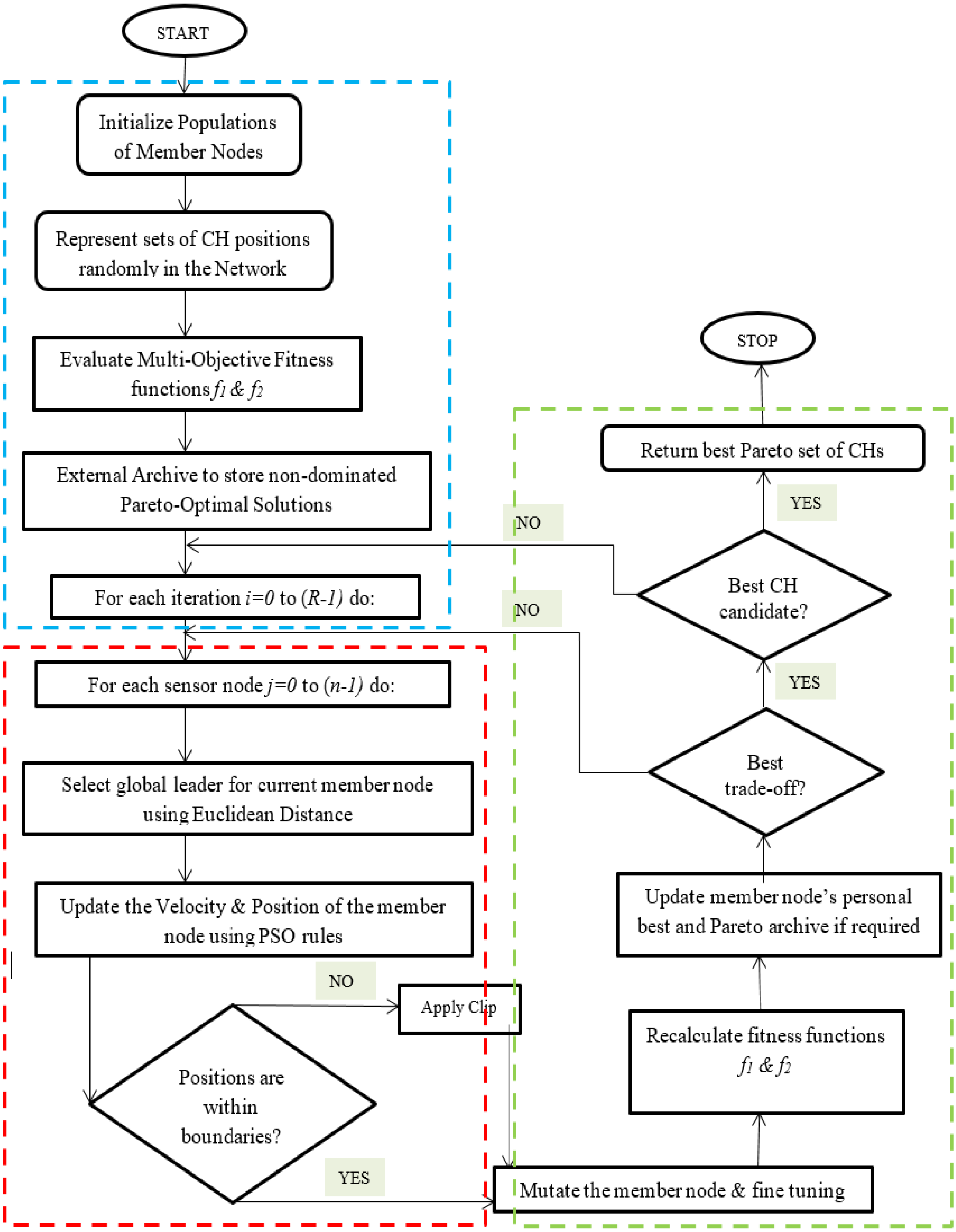

Figure 4. Workflow of the proposed *MOPSO* algorithm for optimal *CH* selection in *WSN-based IoT*.

5. SIMULATION ENVIRONMENT AND PERFORMANCE EVALUATION

Accuracy of the proposed clustering-based algorithm *MOPSO* was assessed through *MATLAB R2019a* simulations executed within a *300 m* × *400 m* wireless sensor network (*WSN*) environment [25, 27, 31]. Sensor nodes were deployed using a flat network topology, with nodes uniformly randomized across the simulation region.

For evaluation, the *MOPSO* technique was compared against three state-of-the-art clustering approaches, namely *EECHS-ARO, HSWO*, and *EECHIGWO*, under identical simulation conditions and parameter configurations. The performance metrics used in the comparison analysis are outlined below.

1. Total number of alive sensor nodes after each round.
2. Total network energy usage.
3. Communication overhead.
4. Total percentage of data packages acknowledged by the destination node.

The simulation network consists of 400 randomly distributed sensor nodes in *300 m X 400 m* region. To provide the best possible communication accessibility, the BS is situated at the coordinates (*145 m, 255 m*). A single-hop communication paradigm is used for data transmission. Each node starts with 1 Joule of battery power and has an equal communication range, but they differ in their energy levels.

7000 simulation rounds were performed to evaluate the network's energy operational stability and energy efficiency. Table 2 lists the simulation criteria and their associated values.

Table 2. Simulation Parameters.

Parameter	Symbol / Unit	Value / Description
Simulation Area	Length X Width (m^2)	300 m X 400 m
Number of Member Nodes	n	400
Base Station Position	BS	(145 m, 255 m)
Initial Energy of Each Node	$Energy_{initial}$	1 Joule
Communication Range	R_c	100 m
Data Packet Size	D_p	4000 bits
Control Packet Size	D_c	200 bits
Transmission Energy	E_T	50 nJ per bit
Reception Energy	E_R	50 nJ per bit
Data Aggregation Energy	E_D	5 nJ per bit per signal
Amplification Energy (Free Space)	ε_{fs}	10 pJ per bit per m^2
Amplification Energy (Multi-Path)	ε_{mp}	0.0013 pJ per bit per m^4
Threshold Distance	z_0	$\sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}$
Number of Clusters	k	20
Maximum Simulation Rounds	R	7000
Optimization Algorithm	—	MOPSO
Benchmark Algorithms	—	HSWO, EECHS-ARO, EECHIGWO
Deployment Model	—	Random (flat topology)
Communication Model	—	Single-hop
Simulation Platform	—	MATLAB R2019a

5.1. Network Lifetime

The number of active nodes is an integral statistic for assessing energy efficiency and network sustainability in wireless sensor systems Figure 5. depicts the variance in the count of active member nodes throughout subsequent network cycles. The proposed MOPSO technique is compared to HSWO, EECHS-ARO, and EECHIGWO by considering the total number of active nodes during the different simulation rounds.

After 7000 simulation rounds, the total count of active nodes for each algorithm is evaluated and reported as follows: for EECHS-ARO, it is 38; HSWO, 55; EECHIGWO, 70; and the proposed algorithm, 105. At the end of the simulation, it is found that the proposed algorithm outperforms others by providing the maximum count of alive nodes. The findings show that as energy usage increases, the number of active sensor nodes decreases over time. However, the outlined MOPSO algorithm has a longer network stability period, clearly demonstrating its effectiveness in improving energy efficiency and maintaining balanced load distribution.

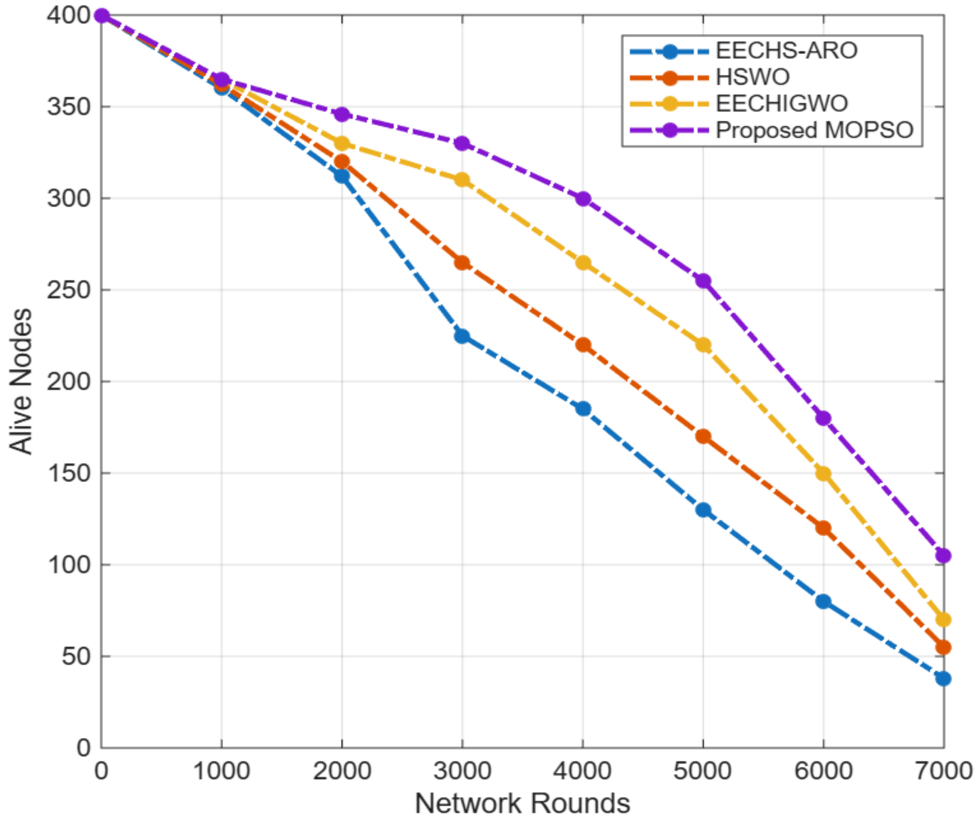

Figure 5. Number of active nodes.

Figure 5 illustrates the total number of alive nodes after each simulation round across different algorithms and the proposed algorithm. Table 3 shows the count of active sensor nodes using various clustering algorithms over multiple network rounds. The number of active nodes gradually decreases as the simulation progresses because nodes deplete their energy from continuous data transmission and reception. The MOPSO-based clustering method outperforms HSWO, EECHS-ARO, and EECHIGWO in terms of node death rates, network stability over time, and energy efficiency.

Table 3. Number of active nodes.

Network Rounds	HSWO	EECHS-ARO	EECHIGWO	Proposed MOPSO
0	400	400	400	400
500	375	368	380	390
1000	362	360	365	365
1500	335	325	348	358
2000	320	312	330	346
2500	290	275	327	340
3000	265	225	310	330
3500	245	205	285	319
4000	220	185	265	300
4500	196	150	240	262
5000	170	130	220	255
5500	140	100	175	195
6000	120	80	150	180
6500	85	55	122	147
7000	55	38	70	105

5.2. Average Energy Consumption

The average energy consumption of various optimization-based routing algorithms based on various network rounds is compared in Table 4. The findings show that the MOPSO protocol performs better in terms of energy efficiency than current methods. Sensor nodes use more energy as network rounds increase due to constant data transmission and reception. MOPSO increases the network's lifespan and energy sustainability by optimizing the cluster head (CH) selection process and distributing energy more fairly among sensor nodes. The average energy consumption of each individual node as the simulation process progressively increases for various algorithms and the suggested algorithm is shown in Figure 6.

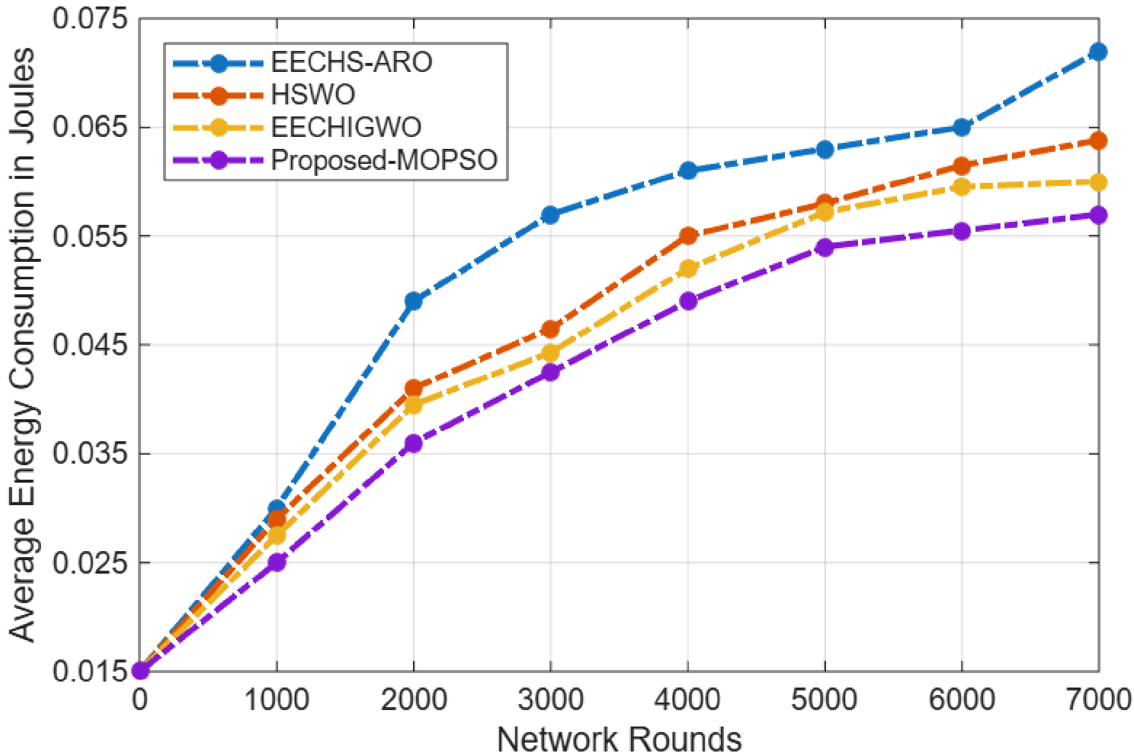

Figure 6. Average energy (in joules) consumption.

Table 4. Average Energy (in joules) consumption.

Network Rounds	HSWO	EECHS-ARO	EECHIGWO	Proposed MOPSO
0	0.015	0.015	0.015	0.015
1000	0.029	0.030	0.0275	0.0250
2000	0.041	0.049	0.0395	0.0360
3000	0.0465	0.057	0.0443	0.0425
4000	0.055	0.061	0.052	0.049
5000	0.058	0.063	0.0572	0.054
6000	0.0615	0.065	0.0595	0.0555
7000	0.0638	0.072	0.060	0.0570

5.3. Communication Overhead (%)

To ascertain the operational efficiency and scalability of the proposed MOPSO protocol, its communication overhead is evaluated and contrasted with protocols HSWO, EECHS-ARO, and EECHIGWO. While keeping the deployment area constant, the study is conducted by varying the total number of installed sensor nodes. While Table 5 presents the corresponding average overhead values for each clustering strategy, Figure 7 shows the variation in communication overhead across various node densities.

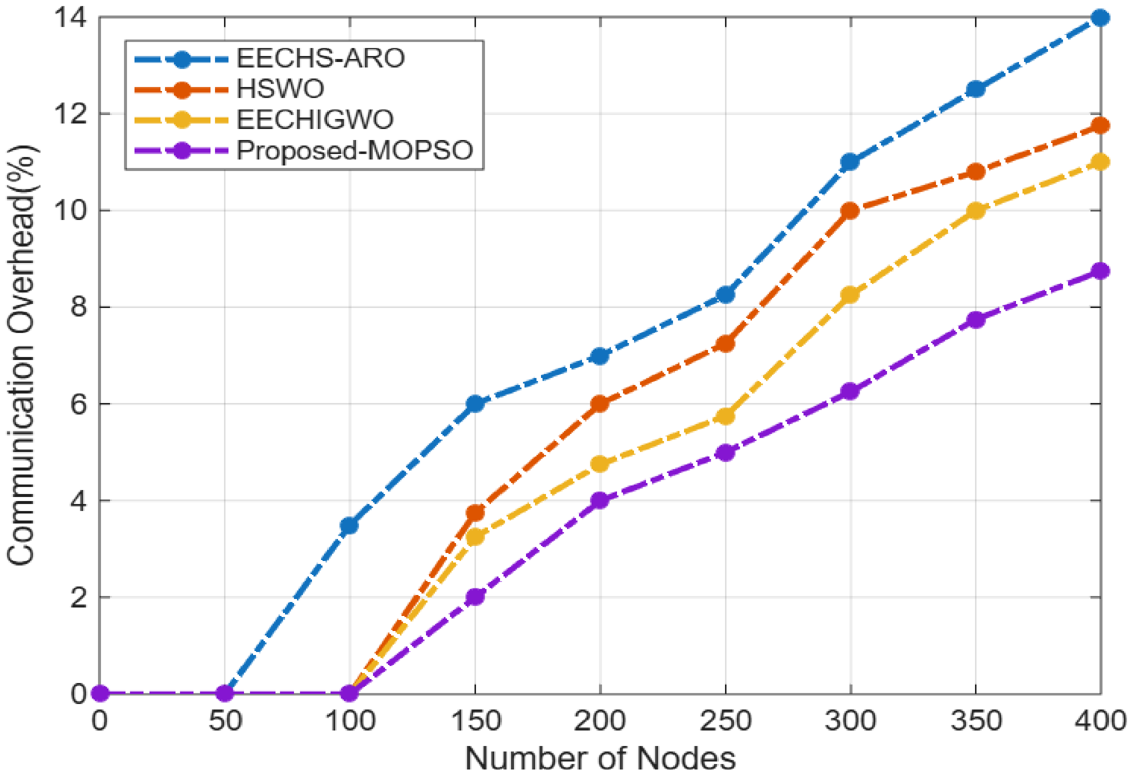

Figure 7. Communication Overhead (%).

In a network deployment with 400 sensor nodes, the communication overhead observed for different conventional protocols are- for EECHS-ARO is 14%, for HSWO is 11.75%, for EECHIGWO is 11% and for proposed protocol is 8.75%. Figure 7 depicts the communication overhead perceived for different protocols. Compared to HSWO, EECHS-ARO, and EECHIGWO, proposed MOPSO protocol reduces communication overhead to approximately 5.25%, 3%, and 2.25%, respectively. These findings demonstrate that the MOPSO-based clustering technique efficiently reduces network overhead by using adaptive cluster-head (CH) selection and dynamic CH rotation mechanisms, resulting in lesser transmission of redundant control packets. Table 5 shows that communication overhead for all approaches increases with node density due to increased coordination between nodes. The proposed MOPSO protocol improves communication efficiency in densely deployed wireless sensor networks by increasing at the lowest rate.

Table 5. Communication overhead (%).

Number of Nodes	HSWO	EECHS-ARO	EECHIGWO	Proposed MOPSO
0	0	0	0	0
50	0	0	0	0
100	0	3.5	0	0
150	3.75	6	3.25	2
200	6	7	4.75	4
250	7.25	8.25	5.75	5
300	10	11	8.25	6.25
350	10.8	12.5	10	7.75
400	11.75	14	11	8.75

5.4. Average Packet Delivery Ratio to the Base Station

The packet delivery ratio to the BS versus the quantity of packets sent by the member nodes is compared and presented in Figure 8 for different protocols and the proposed protocol. The evaluation is carried out within a specific network area to determine data transmission reliability under long-term operational conditions.

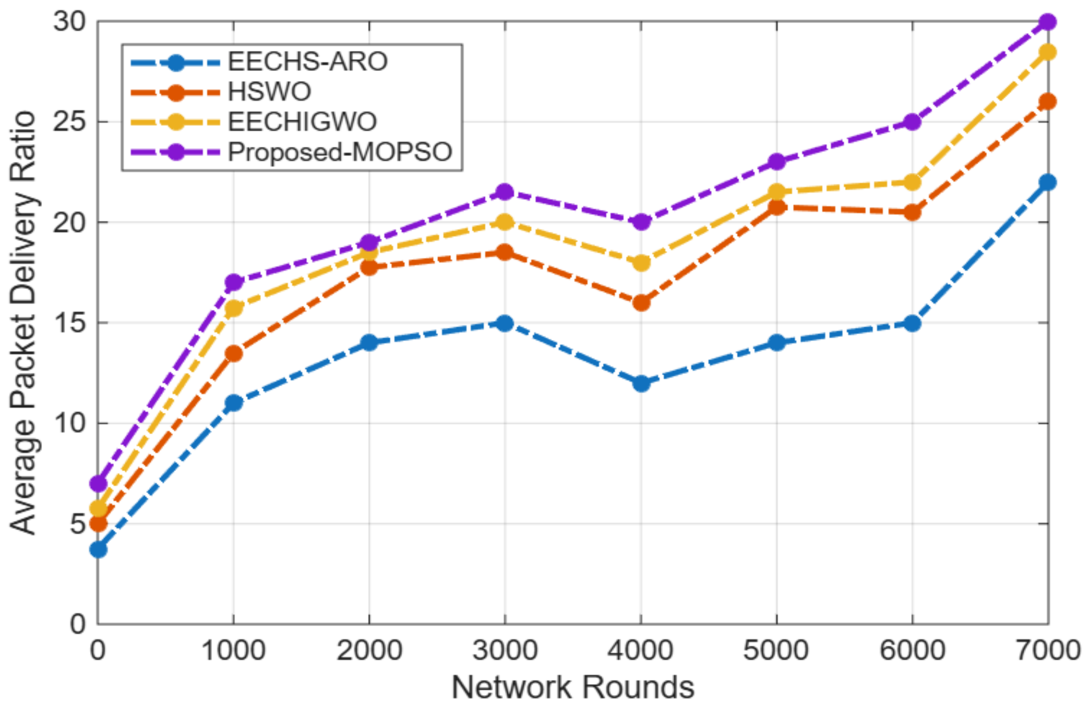

Figure 8. Average packet delivery ratio.

After 7000 simulation rounds, in EECHS-ARO, the ratio is observed as 22, in HSWO as 26, in EECHI-GWO as 28.5, and for the proposed protocol is the maximum as 30, which clearly states that the proposed MOPSO protocol outperforms each conventional protocol for delivering the packets correctly and without any loss.

These findings demonstrate that by choosing energy-efficient cluster heads and guaranteeing balanced data transmission throughout the network, the MOPSO-based clustering mechanism improves packet delivery dependability. Consistent data transmission to the base station is made possible by the adaptive CH selection technique, which also reduces packet loss. Figure 8 shows the proposed protocol's resilience and effectiveness compared to current optimization-based clustering techniques by maintaining superior packet delivery performance even as network rounds increase.

Table 6 summarizes the performance of conventional protocols with the proposed protocol concerning the average delivery ratio. The number of packets arriving safely at the BS appears to increase substantially as the network rounds progress.

Table 6. Average packet delivery ratio.

Network Rounds	HSWO	EECHS-ARO	EECHIGWO	Proposed MOPSO
0	5	3.75	5.75	7
500	9.3	5.75	11.5	12
1000	13.5	11	15.75	17
1500	15.25	12.25	16.2	17.6
2000	17.75	14	18.5	19
2500	18.2	14.55	19	20.5
3000	18.5	15	20	21.5
3500	17.7	13.75	19.2	21.75
4000	16	12	18	20
4500	18.75	12.9	20.3	22.5
5000	20.75	14	21.5	23
5500	20.6	14.75	21.75	24
6000	20.5	15	22	25
6500	23	18.5	25	28
7000	26	22	28.5	30

6. RESULTS AND DISCUSSIONS

Intra-cluster distance, average energy consumption, network lifetime, and the total number of alive nodes after 7,000 simulation iterations were used to measure the performance of the proposed approach. The proposed methodology was utilized to model a network in which sensor nodes are deployed, and the base station control signaling is applied to choose a cluster head (CH). The experiment results indicate that the suggested algorithm has the largest number of active nodes, with 105 nodes remaining active at the conclusion of the simulation. In addition, the mean energy consumption is minimized to 0.0570 Joules, and the communication overhead is also minimized to 8.75%, which is less than that of current techniques. Moreover, the proposed protocol also attains the highest rate of packet delivery to the base station, which means data is delivered effectively and reliably. The findings are depicted in Figure 5 to Figure 8 and tabulated in Table 3 to Table 6. The experimental results achieved by the proposed protocol of MOPSO-based clustering demonstrate the protocol's efficiency in optimizing energy consumption and communication performance. The greater number of alive nodes and reduced power consumption contribute to a longer network lifespan, while lower communication overhead indicates efficient control signaling. Additionally, the higher packet delivery ratio confirms high-quality data transfer without packet loss. The proposed model effectively overcomes limitations of current protocols such as HSWO, EECHS-ARO, and EECHIGWO, presenting a more robust and energy-efficient wireless sensor network model.

7. CONCLUSION

Energy efficiency is an acute challenge in WSNs because of the restricted battery life associated with sensor nodes. Clustering-based data transmission has proven efficient in minimizing energy consumption and enhancing network longevity. While many existing CH selection methods depend on optimization algorithms, they often undergo prolonged convergence times, leading to rapid energy exhaustion.This article proposes a Multi-Objective Particle Swarm Optimization (MOPSO) technique for optimal CH selection in IoT-enabled WSNs. The approach considers both inter-node distances and residual energy to compute two fitness functions operating in two phases: formation of clusters and Cluster Head selection. Using Euclidean distance, MNs are clustered, and then CHs are selected through the proposed MOPSO technique. Simulations conducted in MATLAB R2019a demonstrate that the proposed algorithm outperforms benchmark methods, including HSWO, EECHIGWO, and EECHS-ARO. The proposed technique achieves improvements of 10.02% in packet delivery rate and 9.68% in network lifetime.

Furthermore, the proposed MOPSO algorithm employs a double exponential adaptive inertia weight to balance exploration and exploitation phases. This effectively determines the optimal number of clusters and assigns high-energy nodes as CHs. Comparative evaluation against EECHS-ARO, HSWO, and EECHIGWO confirms its superior performance in energy efficiency, network longevity, and overall system reliability.

In spite of its promising results, the proposed algorithm currently adopts ideal conditions and doesn't account for practical IoT deployment challenges such as node mobility, dynamic topology changes, communication interruptions, and heterogeneous environments, as the entire work was based on assumptions and simulations only. In the future, the proposed MOPSO structure can be extended to real-time IoT scenarios. Additional performance metrics like mobility, load balancing, security, and fault tolerance should be considered. Furthermore, hybrid optimization techniques could be explored to improve adaptability in large-scale IoT-enabled WSN deployments and enhance CH selection under dynamic network conditions.

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