International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Journal Européen des Systèmes Automatisés
Vol. 58, No. 4, April, 2025, pp. 833-840
Journal homepage: http://iieta.org/journals/jesa

Improved Particles Swarm Optimization Based Clustering Process and Data Transmission for Energy Conservation in Wireless Sensor Networks

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https://doi.org/10.18280/jesa.580417

Received: 18 March 2025
Revised: 19 April 2025
Accepted: 26 April 2025
Available online: 30 April 2025

Keywords:
clustering, wireless sensor networks, routing selection, metaheuristic optimization, energy efficiency

ABSTRACT

Due to battery-operated sensor nodes, wireless sensor networks (WSNs) struggle with energy efficiency. Energy-efficient data transmission and sink routing in WSNs are challenging due to resource constraints. Clustering, on the other hand, may greatly extend network life. Therefore, WSN needs an energy-efficient routing system with optimal route selection. The NP-Hard characteristic of clustering is addressed by this research's cluster-based routing approach employing Improved Particle Swarm Optimisation to increase network lifetime and energy conservation. The proposed IPSO algorithm optimizes the cluster formation process by considering node residual energy, distance to the base station, and inter-cluster communication efficiency. Additionally, an adaptive routing mechanism is integrated to ensure energy-aware data transmission, minimizing energy dissipation across the network. The performance of the proposed IPSO method is evaluated against conventional PSO, LEACH, and other metaheuristic-based approaches in terms of certain parameters and found that IPSO achieves 97.8% of network lifetime, 95.3% of total residual energy, 5.8Mbps of throughput, 99.5% of PDR and 11.4% of energy consumption.

1. INTRODUCTION

Recently, wireless communications have gained prominence due to their strong and versatile capabilities for information transmission. Wireless communications denote the relationship between mobility and connection, utilising the atmosphere as a transmission channel [1]. WSN are the predominant technology among current wireless systems. The operation of wireless sensor networks requires effective computational and energetical operations. In these circumstances, communication protocols serve as systematic frameworks that ensure the efficacy of these activities. A WSN comprises a collection of electromechanical devices spread throughout a specified geographical area. These components can furnish significant insights regarding the region of their distribution. This data is exchanged between network sensors via a transmission channel [2]. Battery management affects wireless sensor performance. Since it influences energy autonomy, this is crucial. Information processing is improved by BSs' centralisation. WSNs term the BS the sink or fusion centre for its aggregation.

Popular routing techniques with intriguing features like scalability and efficiency in communications are cluster-based or hierarchical routing. WSN energy conservation methods include hierarchical routing ideas. Hierarchical processing and transmission are only possible with high-energy nodes [3]. In contrast, low-energy nodes collect data near the aim. Hierarchical routing reduces cluster energy utilisation by aggregating information. Hierarchical routing consolidates processes to reduce sink transmission packet size [4]. Nodes may extend network lifespan and architectural scalability when given tasks. Specialised nodes serve as cluster-based or hierarchical reference points. Scalability matters in WSNs. Early assumptions prevent many routing algorithms from solving this challenge. Cluster-based protocols span the area with one sink and several cluster heads in a typical WSN design [5]. This design limits WSN scalability, resulting in expensive energy use. Increasing the network's nodes or impact breadth causes energy overload and information transmission bottlenecks. Node energy conservation is essential for a good protocol. The goal is to increase battery charging frequency [6]. Recharging is difficult or impossible, thus this is crucial. This system distributes power consumption across nodes utilising internal software processes [7]. Each node performs two tasks in hierarchical routing. These operating modes save energy. When this architecture is used at all levels, cluster head and general sensor transmission modes may be significant [8]. Conversely, optimisation tactics like metaheuristic procedures pertain to techniques capable of addressing complicated systems. These algorithms are based on biological or social events, which might be considered search strategies. The literature presents numerous metaheuristic techniques due to its wide application possibilities [9]. DE, Genetic Algorithms, Artificial Bee Colony (ABC), Gravitational Search Algorithm (GSA), and Grey Wolf Optimiser are metaheuristic systems. No continuity, differentiability, convexity, or beginning conditions are assumed for metaheuristics [10]. These qualities show the main advantages over other optimising methods. Although promising, these methods still create hurdles when used to high multimodal formulations. Consequently, the contributions of this study are as follows:

To develop a hybrid clustering model that leverages PSO to optimize the selection of medoids in K-Medoids, reducing sensitivity to initial medoid selection [11]. Especially, under adaptive K-Medoids-PSO model the number of clusters (K) is dynamically determined instead of being predefined.

To adopt priority-based TDMA scheduler that assigns slots based on QoS parameters such as delay, reliability, and packet size [12].

The subsequent portions of the paper are organised as follows. The related work is detailed in Section 2. Section 3 delineates our clustering algorithm. Section 4 presents the numerical simulations of this methodology in comparison to other established methods. The findings are addressed in Section 5.

2. RELATED WORKS

The implementation of a new and effective dual CH routing technique in the study [13] extends the lifespan of WSNs. The CH selection model uses a modified attack power-based hybridisation of sailfish and whale optimisation (MAP-HSWO) to choose the best paths. In the study [14], Sail Fish (SFO) and Spotted Hyena Optimisation use advanced meta-heuristic techniques. This integrated strategy uses SFO's fast exploration for clustering and CH selection. A modified cheetah optimisation algorithm is used to create an energy-aware cluster strategy (MCOA-EACA) for WSN in the study [3]. The MCOAEACA method clusters WSN nodes and chooses a CH to extend network lifespan. Following cheetah hunting, the MCOA-EACA technique solves WSN challenges with agility and efficiency. Choudhary and Barwar [15] proposed two-phase. First, WSN clustering using reinforcement learning (RL) enables nodes to automatically adjust their clustering methods, making network designs more flexible and efficient. PSO may also be used to choose WSN cluster heads to improve cluster formation. References [16, 17] develop a Metaheuristics Cluster-based Routing Technique for Energy-Efficient WSNs. It uses IABO routing. To find the best WSN routes, the IABO approach uses residual energy and distance factor to create a fitness function. In studies [18-20], CH optimisation is a non-deterministic polynomial (NP) hard problem. The selection of the appropriate routing path enhances both the network's longevity and its energy efficiency. This study presents a strategy that integrates multi-swarm optimisation (MSO), also known as multi-PSO, with Tabu search (TS) methodologies. The proposed system selects efficient cluster heads, hence enhancing routing optimisation and prolonging network lifespan.

Despite significant advancements, several limitations persist in existing WSN clustering and routing techniques. Dual CH routing mechanisms increase computational complexity and may lead to excessive energy consumption if not optimized. Hybrid metaheuristic approaches, such as the combination of Sailfish and Spotted Hyena Optimization, often suffer from local optima stagnation and require extensive parameter tuning. Energy-aware clustering methods inspired by animal behaviors may not adapt well to varying node densities and often lack real-time energy balancing mechanisms. Reinforcement learning-based clustering introduces high computational overhead and requires large training datasets, while PSO-based CH selection is prone to premature convergence. Hence, K-Medoids Improved Particle Swarm Optimization (K-Medoids IPSO) algorithm can be employed. Unlike dual CH-based mechanisms that introduce redundancy and excessive energy consumption, K-Medoids ensures optimal CH selection by minimizing intra-cluster distances and balancing energy distribution among nodes. IPSO further refines CH selection by dynamically adjusting PSO parameters to prevent premature convergence.

3. PROPOSED MODEL

The developed clustering approach uses two evolutionary algorithms. CH and cluster member nodes are selected using PSO. Euclidean distance determines the optimal CH sensor-sink route. Figure 1 demonstrates how the source node sends data to the sink node after finding the optimum CH-sink path.

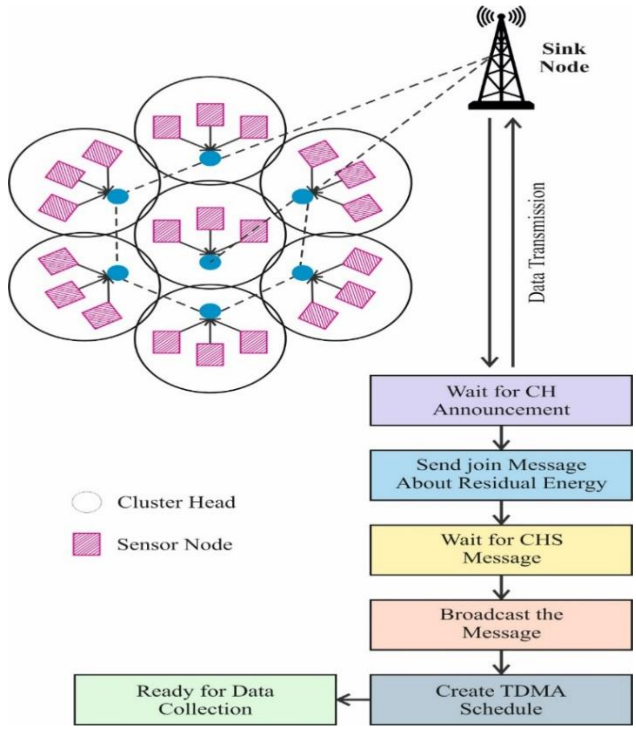

Figure 1. Architecture of the proposed scheme

3.1 Network model

This research analyses the random placement of n sensor nodes in an M×M square area (A). Network premises are as follows.

- All SN share the same beginning energy.
- SN use GPS or other localization technologies to determine their position.
- All SN are fixed after deployment.
- All SN have the same transmission range and are aware of their leftover energy.
- SN modify energy usage depending on receiver distance.
- Each node has a distinct ID.
- The static BS is located at the square area's edge.

3.2 Energy model

Most radio nodes require energy at the transmitter, power amplifier, and receiver. The model employs transmitter-receiver distance-based free space and multi-path fading channels. Node energy consumption is proportional to d^2 if propagation distance d is less than threshold distance d_0, else d^4. Eq. (1) calculates the energy required to convey a l-bit packet d from transmitter to receiver,

$$E_T(l,d) = l.E_{elec} + \begin{cases} l \times \varepsilon_{fs} \times d^2, d < d_0 \\ l \times \varepsilon_{mp} \times d^4, d \geq d_0 \end{cases} \tag{1}$$

where, E_{elec} is the energy used by an SN to send or receive 1-bit data, while ε_{fs} and ε_{mp} are the free-space and multi-path fading amplifier coefficients. Receive energy is given by

$$E_{rx}(l) = l.E_{elec} + E_{wake\_rx} \tag{2}$$

Aggregation energy is given as

$$E_{da}(l) = l.E_{da} \tag{3}$$

Eq. (2) calculates d_0,

$$d_0 = \sqrt{\varepsilon_{fs}/\varepsilon_{mp}} \tag{4}$$

Here, ε_fs and ε_mp are amplifier parameters. The free-space model is used for sensor node energy consumption when $d<d_0$, using ε_{fs} as the amplifier value. Sensor node energy consumption is calculated using the multi-path fading model and amplifier value ε_{mp} when $d \geq d_0$. This study limits node transmission distance to d_0 to guarantee that nodes in the same cluster are within the transmission range of the proposed PSO-based uneven dynamic clustering technique.

3.3 Proposed K-Medoids IPSO based clustering

Each sensor node cluster in the wireless sensor network receives a CH. The BS receives cluster node data from the CH. This work proposes K-Medoids WSN clustering. All sensors are clustered using K-Medoids. Clusters of K-Medoids represent one item. Medoid centres cluster. K-Medoids connected to the cluster node determine the middle and shortest distance between clusters. The sensor nodes communicate better, consume less energy, and detect cluster centres, reducing packet delays. K-Medoids are efficient and converge at step count. K-Medoids IPSO clustering follows these phases:

Step 1: Select k input data points at random.

Step 2: Each data point goes to the cluster with the nearest centre.

Step 3: Add all cluster 'i' data points' distances. Specify the i cluster centre point to reduce estimated distance from other locations.

Step 4: Repeat 1 and 3 until convergence, or the center point stops moving.

Each WSN grouping requires sensor node clustering and CH selection. The CH's major task is sending cluster node data to the BS. Finding precise centroids using K-Medoids reduces power consumption, packet latency, and sensor node performance. The problem is addressed by choosing the bestone from numerous solutions. In PSO, target value or condition, gbest, and stopping value are always recorded. Every PSO particle contains this information:

- Global solution data
- Velocity value indicates data change quantity
- Best value

3.3.1 Cluster formation

The cluster is established by the base station or sink via centralised clustering. The BS sends information gathering messages to all sensor nodes, which send node information to the BS, including node id, location (X and Y distance from the BS), energy loss and energy loss ratio (velocity), and current energy:

Step 1. Transformation of the issue into the PSO framework, whereby each PSO particle has two dimensions: location and velocity.

Step 2. Fitness function valuation. The proposed PSO-based clustering fitness function maximises member node average distance and energy relative to the cluster head and headcount. The formula below calculates particle fitness:

$$fitness\ value = Fv = \propto_I \tag{5}$$

$$= \frac{\sum_{i=0}^{n} d\ (current\ node, member\ i)}{n} + \propto_2 \tag{6}$$

$$= \frac{\sum_{i=0}^{n} E(member\ i)}{E(current\ node)} + (1 - \propto_1 - \propto_2).\frac{1}{\begin{matrix} number\ of\ members \\ covered\ by\ current\ node \end{matrix}} \tag{7}$$

where, $\propto_1$ and $\propto_2$ represent the weighting parameters and n indicates the number of individuals included inside the cluster.

Step 3. New particle formation from solution. Creating new particles from existing ones is novel particle generation.

A particle's current velocity is used to estimate its new velocity, which is the rate of change in its position. New velocity is calculated as follows:

$$\begin{aligned} new\ velocity = \omega^{*} old\ velocity \\ + \omega_1(local\ best\ position \\ - current\ best\ position) \\ + \omega_2(global\ best\ position \\ - current\ best\ position) \end{aligned} \tag{8}$$

Here, ω represents the inertia weight, whereas ω_1 and ω_2 denote fundamental tuning parameters of PSO. Inertia weight ω ontrols how much of the previous velocity is retained. A higher value encourages global exploration, while a lower value promotes local exploitation. Cognitive coeffecint ω_1 affects the particle's inclination to return to its favourite spot. Social coeffecient ω_2 guides the particle toward the global best-known position. A commonly used setting includes a constriction factor or values such as ω=0.729, $\omega_1 = \omega_2 = 1.49445$ ensure convergence stability.

The estimation of the particle's new location is as follows:

$$new\ position = old\ position + new\ velocity \tag{9}$$

Step 4. The fitness function in Step 2 calculates the fitness value for new particles using their velocity and position.

Step 5. The following iteration uses the best particle fitness value from the old and new ones.

New fitness value > previous fitness value

select new particle

else

old particle is forwarded to next iteration

Step 6. There is one local best answer every iteration. The particle having the highest fitness in the current iteration is the local optimal solution.

Step 7. The particle's global best solution is its maximum local best solution throughout all repetitions. Solutions cluster. SN receives a base station cluster-announcement message that creates the cluster via PSO. Every node begins a CH selection cycle after receiving this message. Each CM chooses a CH to form efficient and balanced clusters based on a unique cost function that considers distance to CH, residual energy, and CH member deviation, illustrated as:

$$cost_t = \frac{Eres(i)}{D_{t0}CH(j) \times \left| ND(CH_j) - \frac{\sum_{j=1}^{k} ND(CH_j)}{k} \right|} \quad (10)$$

where, D_t0 CH(j) represents the distance among CM(i) and its candidate (CH)_j, and k represents the number of CHs. Additionally, ND(CH_j) represents CM(i)'s candidate's node degree. First, the final picked CH broadcasts its ID and node degree inside its communication range. The node degree is unitless, but it is being multiplied by a cost term with energy units (e.g., Joules/bit). Each CM estimates cost. The CM will proclaim itself as a CH when k=0, meaning no CH message is received. Therefore, optimum clusters are constructed with higher-cost CHs and CMs. Data transfer after cluster formation is particularly important for WSN energy saving since inappropriate transmission causes failure or collision. Transmission from CMs to CHs using time division multiple access (TDMA) improves these issues.

Algorithm 1: Clustering using K-Medoids with a Particle swarm optimization

Network Initialization

Step 1: Initialize of the WSN S={s1,s2,…sn}

Step 2: Place BS at (50, 180)

Step 3: Place all the SNs

K-Medoids clustering and IPSO CH selection, initiate initial K range: K ∈ [2, 5]

S: Number of swarms; 4 particles

P: Number of particles in each swarm;

X × Y: Dimensions of network terrain

Maximum iteratens=5

Position X_i and velocity V_i for each particle (node) i

Randomly initialize k- medoids (candidate cluster heads) for each particle

Calculate the euclidian distance and compute fitness function for each particle

fitness=∑_(i=1)^k ∑_(s_j ϵC_i) d(s_j,mediod (i)

Update velocity for each particle and find new position

Convergence criteria: No significant improvement in fitness over T iterations, Minimal shift in medoid locations.

Termination based on stability**:** Stability of k over iterations

If stopping criteria are met then terminate. Otherwise, go back to Step 2

Finalize optimal medoids as cluster heads and start data transmission by schedulling

3.4 Data transmission process by scheduling

When many CH nodes carry a packet of data, it will collide, and forwarding to a less-than-ideal CH node diminishes WSN efficiency. We must give each CH node a forwarding priority and ensure that the best one may send packets first to enable packets to go via the worldwide optimum routing channel and avoid packet collisions. A greater U value results in a shorter holding time in this technique. For temporal efficiency, we employ data transfers between neighbouring nodes, consider node i's relative U value, and create as:

$$f(U) = \begin{cases} U - U_{last}, U < U_{last} \; such \; that \; U < 0 \\ 0, U \geq U_{last} \end{cases} \quad (11)$$

where, U_last is the ideal relay node sender's last transmission U value. The minimum propagation delay (t_(max)) with propagation speed v is

$$t(max) = \frac{R}{v} \quad (12)$$

The waiting time ensures that node 2 receives the packet from node 1 before passing it and reduces duplicated transmission.

$$\delta \geq tanh[-f(U_1)] - tanh[-f(U_2)] \quad (13)$$

The retention duration of each node *i* is determined by

$$t_i = tanh[-f(Q_i)].\left(\frac{2t_{max}}{\delta}\right) \quad (14)$$

Initially, devices with 0 or less energy were considered dead and unable to deliver data. If they are in the base station's transmission range and have the highest U-value in their region, devices may connect directly without an intermediate device. If the CH is likewise far away, devices remote from the base station may nevertheless submit packets to it via a neighboring cluster device.

4. PERFORMANCE ANALYSIS

This section examines the parameters of the sensing nodes' results using the proposed method. The effectiveness of wireless sensing networks using the Enhanced Improved Particle Swarm Optimization (IPSO) is compared with other existing known algorithms, including MAP-HSWO [13], SFO+SHO [14] and MCOA-EACA [3]. Based on thorough modeling tests with virtual sensor nodes, the IPSO algorithm improves packet delivery and energy efficiency. The method should be simulated to evaluate its efficiency. The simulation used MATLAB. Windows 7, 4-GB RAM, and Cori3-4160 CPU were utilized to simulate the developed method. The simulation included two situations. Sink node positions in scenarios 1 and 2 are (50, 100 and 50, 200). According to the results, Table 1 lists factors for energy reduction.

Table 1. Experimental values

Parameters	Values
Number of Nodes	200
Size of Network	100*100
Energy Required for Transmitting	40 nJ/bit
Energy Required for Receiving	20 nJ/bit
Energy Required for Sensing	12 nJ/bit
Radius of Sensor	60
Size of Packet	50 Bytes

- **Network lifetime –** It refers to the duration until the first node depletes its energy to transmit a packet, since the loss of a node may result in diminished network functionality.

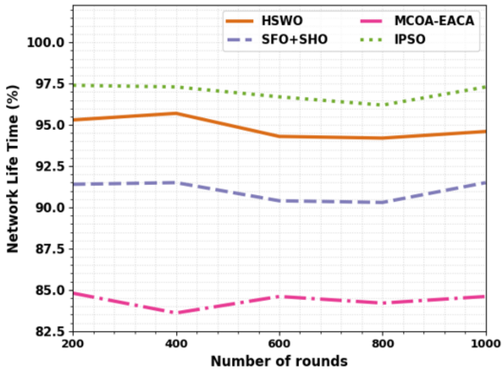

Figure 2. Graphical representation of the network life time

Figure 2 indicates network lifetime, with number of rounds in the x-axis and network lifetime in the y-axis. The existing HSWO, SFO+SHO, MCOA-EACA achieves 95.3%, 90.95 and 84.3% wherein IPSO achieves 97.8%. When analysis the proposed IPSO achieves 2.5%, 7.1% and 13.6% better than aforementioned existing methods.

- Total residual energy – Residual energy deviation is the difference between the nodes with the highest and lowest residual energy divided by the initial energy. This percentage is determined as follows:

$$D_R(t) = 100\left(\frac{E_{max}(n,t) - E_{min}(n,t)}{\sum_{i=1}^{N} E_0(n_i)}\right) \tag{15}$$

In round t, the nodes with the highest and lowest residual energy in the network are E_max (n,t) and E_min (n,t).

Figure 3 compares total residual energy by round count (x) and residual energy (y). The existing HSWO, SFO+SHO, MCOA-EACA achieves 90.8%, 92.3% and 82.4% wherein IPSO achieves 95.3%. When analysis the proposed IPSO achieves 5.5%, 3%, and 13.1% better than aforementioned existing methods as shown in Table 2.

Table 2. The below is the comparison of the network life time (%) of existing techniques and the proposed method (IPSO)

Number of Rounds	HSWO	SFO+SHO	MCOA-EACA	IPSO
200	95.3	91.4	84.8	97.4
400	95.7	91.5	83.6	97.3
600	94.3	90.4	84.6	96.7
800	94.2	90.3	84.2	96.2
1000	94.6	91.5	84.6	97.3

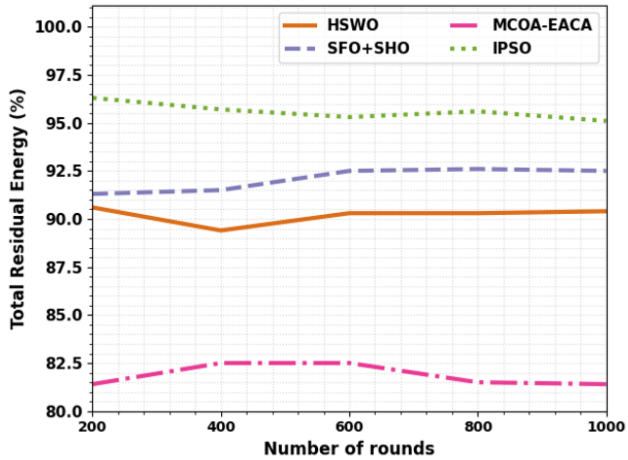

Figure 3. Graphical representation of the total residual energy (%)

Table 3. The below is the comparison of the total residual energy of existing techniques and the proposed method (IPSO)

Number of Rounds	HSWO	SFO+SHO	MCOA-EACA	IPSO
200	90.6	91.3	81.4	96.3
400	89.4	91.5	82.5	95.7
600	90.3	92.5	82.5	95.3
800	90.3	92.6	81.5	95.6
1000	90.4	92.5	81.4	95.1

- **Throughput –** It's important to compare the total amount of packets transferred to the destination node to the simulation procedure's stop time (s_p) and start time (s_t). The mean throughput for k trials is derived from the following equation.

$$throughput = \frac{1}{k}\frac{\sum_{i=1}^{n} X_i \times P_s}{s_p - s_t} \times \frac{8}{100} \tag{16}$$

where, the packet size is P_s. More throughput will be given to an algorithm that delivers the same amount of bits faster.

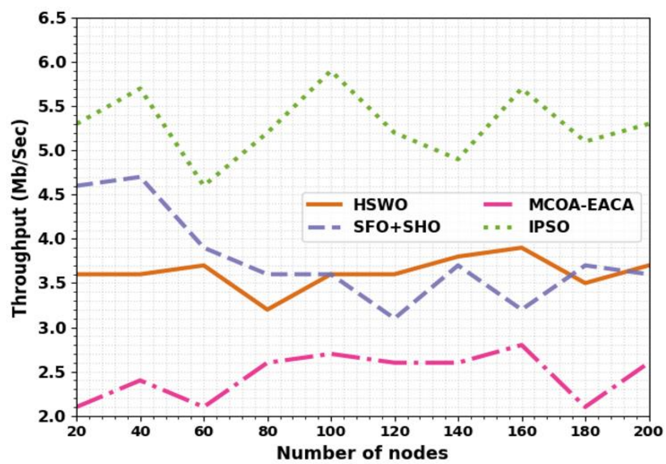

Figure 4. Graphical representation of the throughput (Mb/sec)

Figure 4 indicates throughput, with number of rounds in the x-axis and throughput in the y-axis as shown in Table 3.

The existing HSWO, SFO+SHO, MCOA-EACA achieve 3.6Mbps, 3.5Mbps and 2.8Mbps wherein IPSO achieves 5.8Mbps. When analysis the proposed IPSO achieves 2.2Mbps, 2.1Mbps and 3Mbps better than aforementioned existing methods as in Table 4.

- **Packet delivery ratio (%)** – The percentage of data transmitted to the sink node is calculated using PDR. WSNs compute it by dividing packets transmitted to sink node by data.

$$PDR = \frac{\sum_{i=1}^{n} M_i}{\sum_{i=1}^{n} N_i} \times 100\% \tag{17}$$

where, M represents the received data packets, whereas N symbolizes the sent packets inside the network.

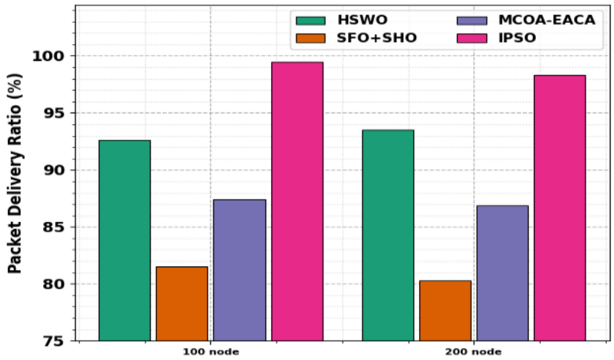

Figure 5. Graphical representation of the packet delivery ratio (%) with nodes

Figure 5 indicates PDR, with number of rounds in the x-axis and PDR in the y-axis. The existing HSWO, SFO+SHO, MCOA-EACA depending in the values showed in Table 5.

Table 4. The below is the comparison of the existing techniques and the proposed method (IPSO)

Number of Nodes	HSWO	SFO+SHO	MCOA-EACA	IPSO
20	3.6	4.6	2.1	5.3
40	3.6	4.7	2.4	5.7
60	3.7	3.9	2.1	4.6
80	3.2	3.6	2.6	5.2
100	3.6	3.6	2.7	5.9
120	3.6	3.1	2.6	5.2
140	3.8	3.7	2.6	4.9
160	3.9	3.2	2.8	5.7
180	3.5	3.7	2.1	5.1
200	3.7	3.6	2.6	5.3

Table 5. The below is the comparison throughput of the existing techniques and the proposed method (IPSO)

Number of Nodes	HSWO	SFO+SHO	MCOA-EACA	IPSO
100 nodes	92.6	81.5	87.4	99.5
200 nodes	93.5	80.3	86.9	98.3

The values of Table 6 presented in Figure 6 which indicates PDR, with number of rounds in the x-axis and PDR in the y-axis. The existing HSWO, SFO+SHO, MCOA-EACA achieves 93.1%, 81.6% and 87.3% wherein IPSO achieves 99.5%. When analysis the proposed IPSO achieves 6.4%, 23% and 12.2% better than aforementioned existing methods.

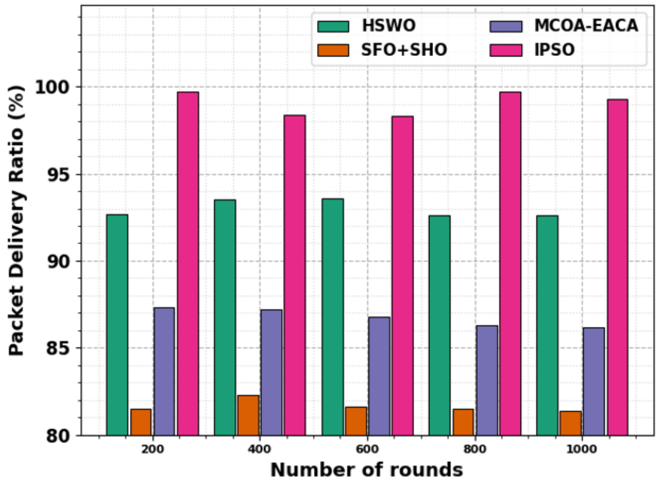

Figure 6. Graphical representation of the packet delivery ratio (%) with number of rounds

Table 6. The below is the comparison PDR of the existing techniques and the proposed method (IPSO)

Number of Rounds	HSWO	SFO+SHO	MCOA-EACA	IPSO
200	92.65	81.5	87.3	99.7
400	93.5	82.3	87.2	98.4
600	93.6	81.6	86.8	98.3
800	92.6	81.5	86.3	99.7
1000	92.6	81.4	86.2	99.3

- **Energy consumption:** The energy consumed when transmitting data. The outcome is contingent upon the transmission power, the duration of the transmission, and the energy efficiency of the radio module.

$$E_{trans} = P_{trans} \times t_{trans} \tag{18}$$

where, E_{trans}=Energy consumed during transmission, P_{trans} transmission power, t_{trans} duration of transmission.

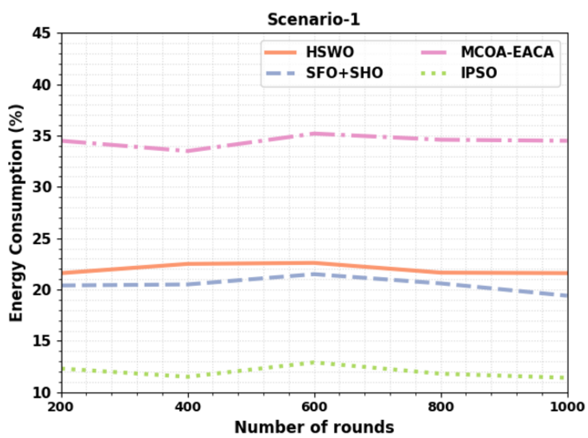

Figure 7. Graphical representation of the energy consumption (%) with number of rounds

The values in Table 6 used in Figure 7 HSWO follows with a steady performance between 94% and 96%, while SFO+SHO maintains around 90%, reflecting moderate efficiency for scenario-1. In contrast, MCOA-EACA shows the lowest performance, with network lifetime ranging between 83% and 85%, suggesting poor energy management.

Table 7. The below is the comparison energy consumption of the existing techniques and the proposed method (IPSO)

Number of Rounds	HSWO	SFO+SHO	MCOA-EACA	IPSO
200	21.6	20.4	34.5	12.3
400	22.5	20.5	33.5	11.5
600	22.6	21.5	35.2	12.9
800	21.65	20.6	34.6	11.8
1000	21.6	19.4	34.5	11.4

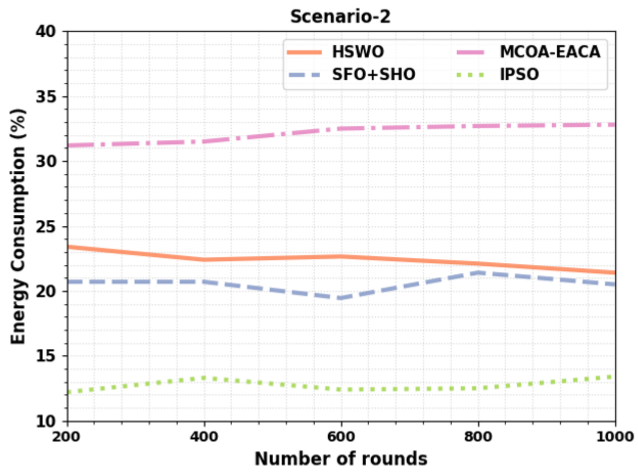

Figure 8. Graphical representation of the energy consumption (%) with number of rounds

In Figure 8, based on the values in Table 7 show the comparison of energy consumption across multiple rounds reveals that the IPSO algorithm achieves the lowest consumption, maintaining values around 12% to 14%, indicating exceptional energy efficiency. HSWO and SFO+SHO exhibit moderate energy usage, averaging between 21% and 24%, with minor fluctuations across rounds. In contrast, MCOA-EACA consistently consumes the most energy, with values ranging from 30% to 33%, suggesting inefficient resource utilization for scenario-2.

The comparison of the existing techniques and the proposed method (IPSO) is shown in Table 8.

Table 8. The below is the comparison energy consumption of the existing techniques and the proposed method (IPSO)

Number of Rounds	HSWO	SFO+SHO	MCOA-EACA	IPSO
200	23.4	20.7	31.2	12.2
400	22.4	20.7	31.5	13.3
600	22.65	19.45	32.5	12.4
800	22.1	21.4	32.7	12.5
1000	21.4	20.5	32.8	13.4

The below Table 9 and the graph sketch the overall performance of the existing and the proposed techniques in Figure 9 and sketch the overall graph for the proposed techniques (IPSO) with the highest network lifetime 2.5% and with the total residual energy increase of 3.0% and the throughput increases with the ratio of 2.3% and the packet delivery ratio increase with 6.3% and with the less energy consumption of 21%.

Table 9. The below is the overall comparison of the existing techniques and the proposed method (IPSO)

Parameters	HSWO	SFO+SHO	MCOA-EACA	IPSO
Network lifetime (%)	95.3	90.9	84.3	97.8
Total residual energy (%)	90.8	92.3	82.4	95.3
Throughput (Mbps)	3.6	3.5	2.8	5.8
Packet delivery ratio (%)	93.1	81.6	87.3	99.5
Energy consumption (%)	21.6	19.4	34.5	11.4
Computational load (%)	32.6	26.8	21.6	13.5
Memory usage (%)	16.6	18.4	26.9	9.4

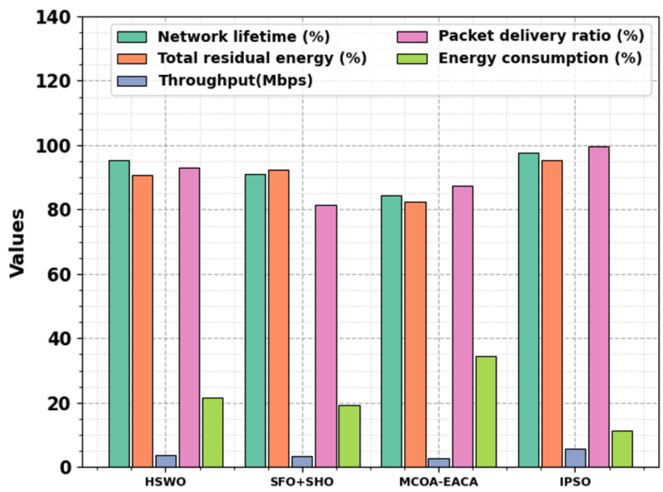

Figure 9. Graphical representation of the energy consumption (%) with number of rounds

5. CONCLUSION

The provision of an energy-efficient routing method is one of the most significant issues in WSNs. This research presents a cluster-based routing system to enhance network longevity. The ideal cluster head selection is contingent upon several criteria, including remaining energy, available buffer, and distance. The PSO-based clustering technique assigned members to each CH based on the smallest distance between SNs and the CH and the most residual energy. The ideal path selection between the cluster head and the sink, characterized by energy efficiency, was ascertained by Euclidean distance. The comparison of the developed technique with existing schemes demonstrates superior network performance of the proposed method. This project will focus on creating an energy-efficient, cluster-based routing algorithm utilizing suitable hybrid metaheuristic optimization techniques. In future endeavors, we want to further the developed approach for heterogeneous WSN.

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