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Original Article

ASWDR Compression Scheme Assisted PSO Based Energy Aware Routing Scheme for Internet of Things (IoT) Application in WSN Scenario

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Abstract *- Modern high-speed communication devices require efficient network architecture with energy usage constraints. This requirement introduced the application of IoT, which represents a new milestone in the prevalent global use of advanced devices. This article proposes a novel routing protocol by using a simulation environment for a homogeneous Wireless Sensor Network (WSN), applying the optimization algorithm with data compression at cluster heads during the data aggregation phase to assist the cluster head allocation process. An optimized mechanism for selecting cluster heads is employed on the current best solutions and the global best solution to perform transmission of sensor data. A new energy-efficient routing technique has been presented to increase the operating lifetime of sensor node-based IoT networks. The suggested protocol shows a remarkable reduction in the sensor nodes' average energy consumption when compared to conventional techniques, which ultimately results in a longer network lifetime. In particular, the proposed approach provides a 60% improvement over conventional protocols such as LEACH or PEGASIS in terms of the time taken at the round associated with the first node being discharged (dead) metric and a 20% increase over the optimized DEEC WSN routing protocol in terms of energy efficiency.*

Keywords *- IoT, WSN, Clustering, PSO, Data compression, Wavelet Transform.*

1. Introduction

IoT seeks to improve human well-being by creating smarter, more automated, and more efficient environments across a variety of businesses [1, 2]. With its effect quickly spreading into industries including environmental sensing, smart homes, and healthcare services, IoT serves as a major catalyst in the current industrial revolution [3-5].

These Internet of Things applications frequently use sensor nodes that are put in hostile or unreachable locations where maintenance is not practical and are powered by low-capacity batteries. Energy-conscious IoT solutions are becoming more and more in demand [6-8].

The foundation for wireless communication in these systems is provided by WSNs, a critical section for IoT infrastructure [9]. Clustering methods are frequently used in WSNs to increase energy efficiency and extend network operation, providing notable performance gains to the evolution of the IoT paradigm [10-12]. Cluster Heads (CH) are key components in clustering techniques because they collect sensor data from all nodes [13, 14]. The importance of coverage, node centrality, and residual energy are among the characteristics considered while selecting CHs [15, 16]. One of the key goals in this area is to identify an effective strategy for tackling multi-criteria decision-making issues [17, 18]. Communication is the most energy-intensive activity done by sensor nodes, significantly beyond that of sensing or data processing [19, 20].

Nodes located far from a static sink frequently use single-hop communication, which costs a lot of energy [21]. In contrast, nodes closer to the static sink are burdened by significant multi-hop data relay, resulting in rapid energy depletion [22].

This mismatch leads to the energy-hole issue [23, 24]. Notably, collecting data from each sensor node independently entails substantial delay, which presents a difficulty for applications that require quick reaction. To overcome this, a feasible method is to pause the Mobile Sink (MS) at specified points rather than contacting each node individually [25].

However, this strategy might result in higher control overhead owing to frequent topology reconstructions [26]. To address issues with energy usage in WSNs, the Energy-Efficient Geographic Routing Protocol with Mobility in Sink (EGRPM) was developed [27].

Table 1. Summarized literature review

Ref. No.	Author (et al.) / Year	Approach	Limitation	Benefits
[8]	Wason et al., 2021	Smart sensor networks with IoT	Security and scalability concerns	Supports real-time smart applications
[9]	Yin et al., 2022	Survey of LEACH-based clustering	Focused mainly on the LEACH family	Identifies research gaps; highlights improvements
[11]	Mugerwa et al., 2023	Hybrid distributed clustering with multiple sinks	High complexity due to multiple sinks	Enhanced energy efficiency; scalability
[12]	Sobin, 2020	Survey on IoT architectures & protocols	Broad overview; lacks case studies	Identifies IoT challenges and open issues
[13]	Shafique et al., 2020	Review of IoT-based smart applications	Generalized analysis	Future trends and 5G-IoT integration insights
[14]	Babbar & Rani, 2020	SDN framework for IoT security	Overhead in SDN deployment	Enhances IoT network security
[16]	Shahraki et al., 2021	Survey on clustering: WSN to IoT	Theoretical review	Explores clustering trends across paradigms
[20]	Darabkh et al., 2022	Allocation of time slots to energy constraints in IoT	Limited applicability in highly dynamic networks	Reduce energy consumption and interference
[21]	Thomson et al., 2021	Energy balancing with a mobile sink	May increase latency	Improves energy balance across nodes
[22]	Amutha et al., 2022	Hybrid optimization with static and mobile sink	More control overhead	Improves energy and reliability
[27]	Naghibi & Barati, 2020	EGRPM: Geographic routing with mobile sink	Limited adaptability in heterogeneous IoT	Reduces the energy hole problem
[29]	Khafaga et al., 2023	Haar Wavelet + COVIDOA compression	Lower compression ratio (25.6%)	Moderate improvement in bio-signal compression
[30]	Bencherqui et al., 2022	Hahn moments + ABC for compression	Higher complexity	15.5% compression; robust reconstruction
[32]	Elyyan & Darabkh, 2023	PRVD protocol with computational intelligence	Moderate energy consumption (0.021 J)	Improves power-limited IoT routing
[33]	Eberhart & Shi, 2001	Particle Swarm Optimization	May get stuck in local optima	Simple, powerful, swarm-based optimization

Static sensor nodes with constrained power resources are dispersed at random within a sensing field divided into square zones of equal size in order for EGRPM to function. These grid cells are divided into two groups: Multi-Hop Communicating Cells (MCCs), which forward data from the Mobile Sink (MS) to the closest MCC node with the most energy left, and Single-Hop Communication Cells (SCCs), which send data straight to the MS without the use of relay nodes. Another option is to transmit data through a nearby SCC if it is within range. The Rendezvous-based Routing Protocol (RRP) [28] conceptually divides the sensor field into eight octagonal pieces.

The virtual rendezvous area is created by dividing the whole network field into a central intersecting zone. This region's nodes are referred to as backbone nodes and are an essential component of the communication network. A portion of the routing tree, which includes a few backbone nodes along its structure, starts with the boundary nodes of the four virtual zones. Every border node calculates how far it is from the network core and determines whether its remaining energy is greater than a certain level. It chooses a nearby node, which has to be a component of the backbone, if these requirements are satisfied.

1.1. Problem Statement

IoT-enabled WSNs suffer from rapid energy depletion due to inadequate selection of CH and high overhead schemes of communication. Existing protocols such as LEACH, PEGASIS, and DEEC either optimize routing or apply compression separately, but fail to address both simultaneously. This results in suboptimal energy efficiency, reduced scalability, and shorter network lifetime.

1.2. Research Gap

Prior studies focused on either meta-heuristic-based CH selection or compression methods like Haar and Tchebichef, achieving limited gains (15–25% compression, modest lifetime improvements). However, no work has jointly integrated PS-based CH optimization with ASWDR compression. This gap motivates the proposed PSOEACASWDR, which significantly enhances compression efficiency, reduces energy consumption, and extends network lifespan.

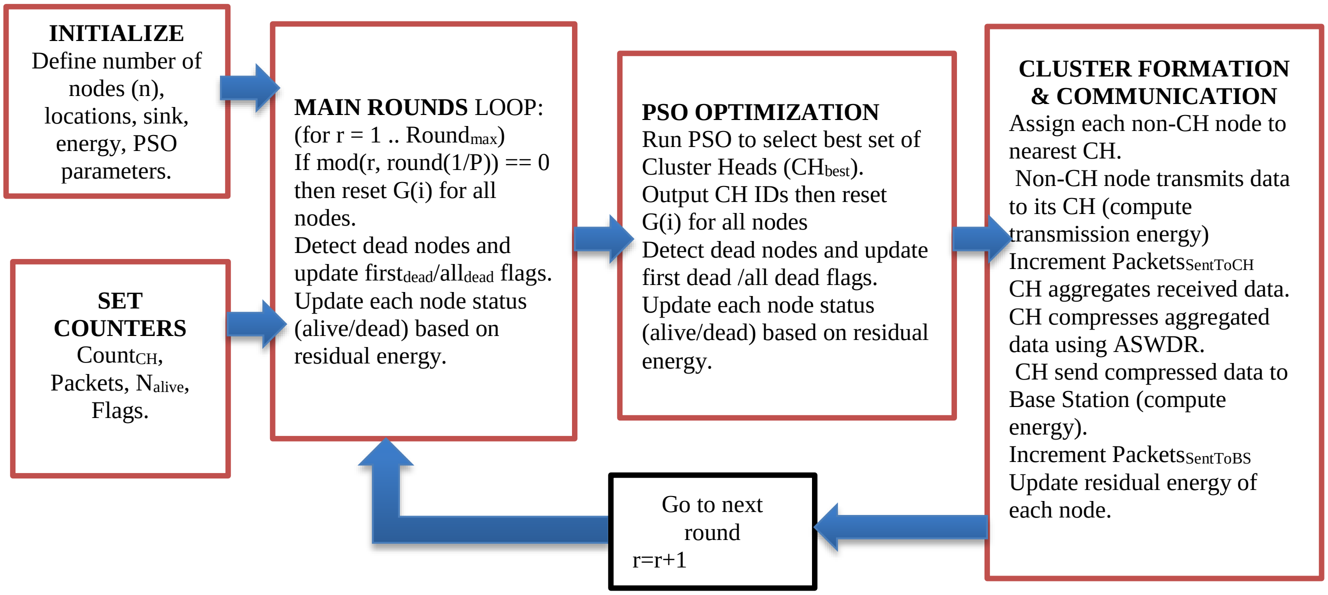


Fig. 1 Block diagram representation of the proposed methodology

1.3. Background

The reviewed literature establishes that existing clustering and routing protocols, such as LEACH, DEEC, and RRP, improve energy balance but still suffer from high consumption and limited lifetime, while compression techniques like Haar, Hahn, or Tchebichef moments achieve only 15–25% efficiency when applied in isolation. Moreover, optimization methods like PSO are proven effective for cluster head selection but have not been integrated with data compression to address both routing and transmission costs simultaneously. These gaps justify the proposed PSOEACASWDR protocol, which holistically combines PSO-based clustering with ASWDR compression to minimize energy use and significantly extend the lifetime of the network under IoT-WSN applications.

In this work, a protocol is proposed to support the selection of an optimum set of CHs and data compression after aggregating data at the selected optimum set of CHs. This strategy offers a power-aware routing technique that makes use of network and node parameters to set the fitness of CHs to choose the best CH IDs. By supporting effective clustering with a fitness function dependent on residual energy and the position of sensing devices, it seeks to lower the consumption of energy and improve IoT networks' overall performance. It efficiently reduces communication overhead and enhances scalability by clustering the WSN. The Particle Swarm Optimization (PSO) method, which clusters nodes and permits data transfer via the DEEC routing system, is used by the protocol to determine the best CHs. Following the cluster-based routing strategy, aggregated data at each CH is compressed using Adaptively Scanned Wavelet Difference Reduction (ASWDR), which further reduces energy consumption and increases network lifespan. The proposed method-based simulation outcomes are compared with those of conventional routing protocols. The article is presented in different sections. In Section II, the methodology is described. Section III discusses the performance in terms of simulation results. The conclusion part is covered under Section IV.

2. Materials and Methods

In order to reduce the consumption of energy during data transmission through the IoT sensor nodes and hence increase network lifetime, this section describes an efficient clustering protocol in conjunction with a structured routing scheme. The goal is to gather and transfer data to CHs. PSO-based Energy-Aware Clustering with ASWDR compression (PSOEACASWDR), the suggested protocol, exhibits excellent network coverage and operational effectiveness, which enhances lifespan. The PSOEACASWDR protocol comprises three stages: (i) Clustering and CH Selection: A fitness evaluation of CH sets based on network characteristics is used to determine the region of interest.

The PSO meta-heuristic algorithm is utilized for increasing the stability and efficient energy consumption of WSN-IoT systems. (ii) Data Compression Phase: In this phase, data gathered at the CHs is compressed using the ASWDR technique prior to transmission to the BS. By doing this action, the energy hole problem is lessened, and energy consumption is decreased. It helps to reduce transmission overhead and stabilizes the dissipation of energy. (iii) Routing phase: A routing method was developed to transmit data to the BS either directly or via the CH to improve the network's overall efficiency. The DEEC, which aims to decrease the consumption of energy and increase the active lifetime of the present CH, is incorporated into this method. It keeps a balanced energy profile by preventing nearby CHs from facing excessive energy loss.

Assumptions considered under the proposed protocol:

- Sensor nodes are placed at random and stay stationary for the duration of their lives.
- All the sensor nodes possess equal energy and do not need to be recharged.
- Transmission energy depends on node-to-node distance.
- BS is fixed and positioned in the middle of the field where the sensing operation is performed.
- The sensing field has subdivisions of several clusters, each of which is monitored by a CH chosen by PSO.
- A single-hop paradigm governs communication between nodes and CHs.

2.1. Network Model

N identical, stationary sensor nodes with uniform capacities are arranged at random within an m × m area as part of this network design. Each node has a GPS unit to identify its location from the center of the field and is given a unique ID (from 1 to N). At first, BS broadcasts 'Hello' messages with its location. Each sensor node responds by sending the closest nearby node its identification number, location, and starting energy level. CH receives this information and is chosen on the basis of higher energy and processing capabilities. CH, who was chosen using the PSO method, was assigned the task of grouping the field into clusters. It is important to note that the protocol is organized into several distinct operating rounds, which guarantee system efficiency and regular updates. Every round, all clusters get data packets from the BS. The list of IoT sensor nodes in the cluster, the CH ID, the locations and energy levels of cluster members, and other specific information are all contained in these packets. Every round has a setup phase and a steady-state phase.

The setup step phase is applied to choose the node at the next hop and manage CH selection. It assigns time slots to sensor clusters for data transmission. Sensor nodes provide data and information, as well as residual energy, to the CHs during the steady-state period. CH uses a TDMA technique to provide a specific transmission time segment for its member nodes to avoid intra-cluster interference. Additionally, each CH uses the Adaptively Scanned Wavelet Difference Reduction (ASWDR) approach for data compression after performing local data aggregation in order to save energy (see Figure 1).

2.2. Cluster Fitness Parameters

The parameters that are considered in this work are listed below:

a) Converging function ($F_{converging}$): It is defined as the sum of distances within the cluster and calculated as the sum of distances of nodes to the CH. A cluster is generated by sorting out the nearest nodes of a given CH. The cluster structure is assumed to be appropriate if the distance of most of the cluster member nodes is near the CH.

b) Diverging function ($F_{diverging}$): Defined as the sum of the distance between two cluster centers. The clusters should be located as far apart as possible. Hence, the center of the clusters should be higher.

c) Centrality of the CH: Factor representing the closeness of CH to the center of the cluster.

d) Node degree: It defines the number of nodes in a cluster divided by the total nodes. A cluster is assumed to be better if it covers a large number of nodes.

e) Distance of Cluster Head (CH) to base station ($D_{CH\text{-}to\text{-}BS}$): The lower the distance of CH to BS, the less data transmission energy consumption will be.

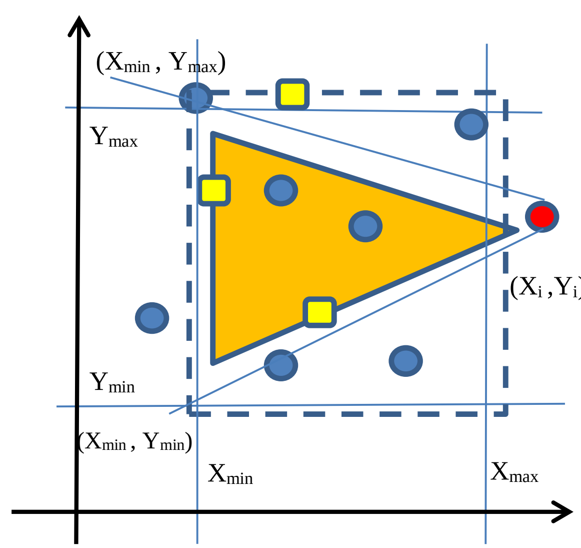
f) Residual energy of the CH ($E_{Res}(CH)$): The selected set of CHs should have higher residual energy.

There are a total of six parameters named as fconv(f1), fdiv (f2), centrality (f3), node degree (f4), DCH-to-BS (f5), and ERes(CH), which have different impact on reflecting the fitness factor of the set of cluster heads some are desired to be large and some are desired to be low. The diverging function and residual energy should be higher for the selected set of CHs, while other factors have a reverse impact on the CH set to be fit for WSN data transmission.

Fitness is directly proportional to: {f_{div}, E_{res}_CH}
Fitness is inversely proportional to:{f_{conv}, Centrality, $Dist_{CH\ to\ BS}$, Node-Degree}

Fitness function= F= f(1/f1, f2, 1/f3, 1/f4, 1/f5, f6)
and scaling factor={a1 to a6}
fitness value=$\sum_{i=1}^{6} F_i * a_i$
= 1/f1*a1+f2*a2+1/f3*a3+1/f4*a4+1/f5*a5+f6*a6 (1.7)

Since all the parameter value f1 to f6 are of different ranges, they are normalized to bring them under a common range by multiplying scaling factors a1 to a6 to maintain equal weightage of each parameter.



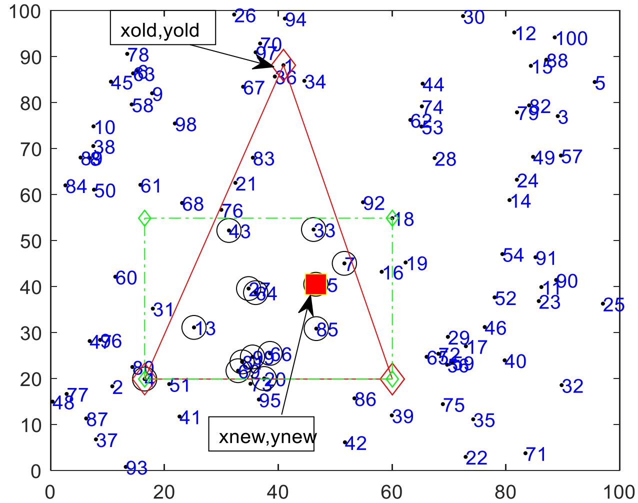


Fig. 2 The approach for updating the CH position to find a better solution (Top) and position update of the current node in the simulation environment (Bottom)

2.3. Particle Swarm Optimization (PSO)

PSO is an evolutionary algorithm that was first presented in 1995 [29] and was motivated by the coordinated movements of fish shoals and bird flocks. This approach models each potential solution as a "particle" that investigates the search domain. The two main determinants of these particles' mobility are their individual best experiences and the swarm's overall best performance.

The position and velocity of each particle are updated using mathematical formulas that incorporate random components, as well as cognitive and social factors. Over time, particles are drawn toward the best solutions found by themselves or their neighbours, allowing the swarm to converge on an optimal or near-optimal solution. The Particle Swarm Optimization (PSO) velocity update formula is:

$$v_{new}=w.v_{current}+c_1.rand_1.(p_{best}-x)+c_2.rand_2.(g_{best}-x) \quad (1.7)$$

Where, v_{new} /$v_{current}$: new or current particle velocity, c1 / c2: coefficient of cognitive or social learning, w: inertia weight. $Rand_1$ or 2: random numbers from 0 and 1, p_{best}/g_{best}: best position (solution) found by the particle so far, and x: particle's current position.

2.4. Distributed Energy-Efficient Clustering (DEEC)

DEEC is an adaptive clustering protocol developed for heterogeneous WSN. Unlike traditional protocols that assume a uniform energy supply, DEEC dynamically adjusts the probability of selecting a node as a CH on the basis of the network's average energy and the node's residual energy. A higher probability is allotted to sensor nodes with higher energy to select as a CH.

This scheme helps balance the energy load in the network area. This strategy avoids overburdening weaker nodes and increases the stability period (the time before the 1st node is dead) and the complete lifetime of the network. DEEC operates in a distributed manner, meaning each node independently determines whether it should become a cluster head without needing global network information. The protocol adapts over time, recalculating energy metrics in each round to ensure efficient use of resources.

Algorithm for selection of CH using PSO along with the data compression step using ASWDR:

PSOEACASWDR

1. Define the number of nodes:n
2. Define a random location of sensor nodes
3. Define the fixed location of the sink node
4. Define $E_{initial}$, $E_{TX/RX}$, $E_{fs/mp}$, $E_{agrregation}$
5. Define a, $Round_{max}$, $D_{threshold}$
   Loop i:1 to n
6. Allot advanced energy randomly
7. $E_{initial}$ (i)= $E_{initial}$*(1+rnd*a) % rnd=random number
8. Allot flag G%G [0, 1], 1 if node is selected as CH
   end Loop i
9. Set $Count_{CH}$, Flag $_{first\ dead}$, Flag $_{all\ dead,}$ $N_{alive\ nodes/dead\ nodes,}$ $Packet_{sent\ to\ BS/CH}$
   Loop r: 1 to $Round_{max}$
10. If (mod(r, round(1/P))==0)%reset flag G at each 1/p rounds
11. Set G(i)=0
    end if
12. Check: count of dead nodes
13. Check: 1st node dead & set/reset flag $Flag_{first\ dead}$
14. Check: All nodes are dead & set/reset flag. Flag $_{all\ dead}$
15. Check: Node energy E_i> 0 % node is alive or not
16. Define PSO parameter: [pop, iter,α] %{population size, number of iterations, Acceleration parameter}
17. Call the PSO optimization algorithm
18. Find the best CH id set: CH_{best} using PSO
19. Find nodes nearest to CH
20. Allot head to the nearest nodes
21. Transmit Data From sensor nodes to the respective CH
22. Calculate the Energy consumed to transmit packet S to CH
23. Count number of packets sent to CH: $Packet_{sent\ to\ CH}$=$Packet_{sent\ to\ CH}$ +1
24. Data aggregation at the respective CH.
25. Data compression at CHs using ASWDR.
26. Transmit Compressed data from CH to BS
27. Calculate the Energy consumed in transmitting a packet from CH to BS
28. Count number of packets sent to BS: $Packet_{sent\ to\ BS}$=$Packet_{sent\ to\ BS}$+1

29. $E_{res}^{i,r} = E_{res}^{i,r-1}$ - Energy consumed $_{\text{to CH and CH to BS}}$% Calculate residual energy of i^{th} node at r^{th} round

end loop r

PSO Algorithm

Input: Lower bound, Upper Bound, Parameters

Parameters: [pop, iter, α]

1. Call Sub Program to Initialize Particle position to get best solution: $PSO_{initialize}$
2. %% Best Solutions : $best_{NCH\ x\ Pop}$
3. Fbest=0 %consider a small value of fitness

Loop i= 1 to iter

Loop j= 1 to pop

4. Xa=Best{i} % Input best particle one by one
5. Find fitness value (f_{val}) for i^{th} best particle
6. If $F_{val\ of}$ i^{th} best particle > Fval of G_{best}
7. Update the best particle

end

end

8. Call Sub Program to update the particle position: PSO_{move}
9. $Xa_{new\ position}$= $Xa_{old\ position}$ + velocity
10. Best{i} =$Xa_{new\ position}$

end

Sub Program: $PSO_{initialize}$

(Initialize Particle position to get the best solution)

Description: Set random cluster head IDs as an initial solution(population)

Input: Pop, lower bound, upper bound, n

1. Generate random value for each node: $temp_{rand}|^{pop\ x\ n}$
2. Calculate probability for selection of node as a cluster head: p
3. p=P*n*(1+a)*E./(n+A)*(Ea)

Loop k=1 to pop% select CH for each particle

4. if $temp_{rand}$<(p./(1-p.*mod(r,round(1./p))))
5. Select the sensor node as CH

end

6. Save the sensor node to CH_{id}

Return: CH_{id} as the Best solution for the first iteration to the PSO algorithm

Sub Program: PSO_{move}

(Update Particle position to get the best solution)

Description: Update the cluster head ids set with respect to the best set of CH ids (best solution)

Input: $best_{current}$, $best_{global}$, pop, α, Lower bound, upper bound

1. Xr, Yr: Get the Location of all the nodes
2. Xr_{gbest}, Yr_{gbest}: Get the Location of all the CH ids of the global best solution
3. Find the minimum/maximum value of x and y co-ordinates of $CHid_{gbest}$ {x_{min},x_{max},y_{min},y_{max}}
4. Set a square region using {x_{min},x_{max},y_{min},y_{max}}

Loop j= 1 to number of nodes in $best_{current}$

5. Local best : L_{best}(j1): get CHids of $j1^{th}$ local best solution
6. Generate triangle with vertices as : [$L_{best}(j1)_{x,y}$, Farthest points of square from $L_{best}(j1)_{x,y}$]
7. Set triangle vertices as : [$x_{\Delta 1}$, $y_{\Delta 1}$, $x_{\Delta 2}$, $y_{\Delta 2}$, $x_{\Delta 3}$, $y_{\Delta 3}$]
8. x/y_{inside}: Find all the sensor nodes inside the triangle
9. Select the nearest node in set x/y_{inside} to $L_{best}(j1)_{x,y}$ as the next best solution
10. Update position $L_{best}(j1)_{x,y}$ by nearest x/y_{inside} : $L_{best}(j1)_{x,y}^{new}$ = nearest x/y_{inside} to $L_{best}(j1)_{x,y}^{old}$
11. $X/Y_{new\ solution}$ = coordinates of updated $L_{best}(j1)_{x,y}^{new}$ % New position of particle
12. Add a new solution with P*n/2 sensor nodes with the highest energy

end

13. Return the updated solution of CH ids to the PSO algorithm

2.5. Adaptively Scanned Wavelet Difference Reduction (ASWDR)

ASWDR is a lossless data compression technique that builds upon wavelet-based image coding. It is an improvement over previous methods like Set Partitioning In Hierarchical Trees (SPIHT) and Embedded Zerotree Wavelet (EZW). ASWDR takes advantage of the sparsity of the wavelet coefficient matrix after transformation and applies adaptive scanning and difference reduction to encode significant coefficients efficiently.

It scans the transformed data adaptively in a way that data blocks with important details are identified, allowing more efficient use of bit resources.

The key idea is to reduce the difference between significant wavelet coefficients and predict their values using spatial context, resulting in better compression performance without losing any data.

2.5.1. ASWDR Working and Role

ASWDR is a lossless wavelet-based compression technique that improves upon earlier methods. The goal of ASWDR is to reduce redundancy in wavelet-transformed data while preserving all original information.

a) Wavelet Transformation: The original sensor data (e.g., temperature, ECG signals, and environmental measurements) is first transformed into the wavelet domain. The wavelet transform generates coefficients that represent the signal in different frequency bands, where many coefficients turn out to be very small or zero (sparse representation).

b) Adaptive Scanning: ASWDR uses an adaptive scan path. It searches for significant coefficients dynamically, focusing on areas where more information (high energy or detail) is present.

Difference Reduction: For significant coefficients, ASWDR does not store the raw value directly. Instead, it predicts values based on nearby coefficients and stores only the difference between the true value and the predicted value; hence, fewer bits are required to encode them.

c) Bitstream Formation: Bitstream is generated in which important coefficients are encoded first, followed by less significant ones.
d) Lossless Decoding: The encoded differences and scanning path are utilized to reconstruct the original wavelet coefficients. An inverse wavelet transform then perfectly restores the original sensor data. In this paper, ASWDR is applied in the data compression phase of the proposed PSOEACASWDR protocol.

The sensor nodes collect data and forward it to the CHs selected by PSO. The CH then aggregates the data before sending it to the BS.

Since communication consumes higher energy than sensing or computation, reducing data size during transmission is critical.

In this work, the DEEC protocol is further extended by incorporating the PSO algorithm for the phase of selecting CHs.

In Figure 2 (top), the Yellow Squares: Global best solution; Blue circle: Stray nodes (possible solution); Red circle: Current solution that is to be updated in position (x_i, y_i); $(X_i, Y_i)_{new}$ will be the node within the best solution triangular space with the highest residual energy.

Distance between xy_i and $gbestxy_i$. Corners of the square are the farthest points from the current best solution under the coordinates of the global best solution representing the set of CH ids. The coordinates of the square are: [(x_{min}, y_{min}), (x_{min}, y_{max}), (x_{max}, y_{min}), (x_{max}, y_{max})].

The particle represents a set of nodes initially taken as a random number of nodes and updated with the nodes with higher fitness value under the space defined in Figure 2 (bottom).

The protocol developed in this article is a combination of PSO and DEEC as PSO-based energy-aware routing (PSOEAC), and it is extended by incorporating data compression using ASWDR (PSOEACASWDR).

3. Results and Discussion

The proposed protocols PSOEAC and PSOEACASWDR are implemented on MATLAB 2019 software as a program for WSN routing from the source node to BS through the optimum solution set of CHs.

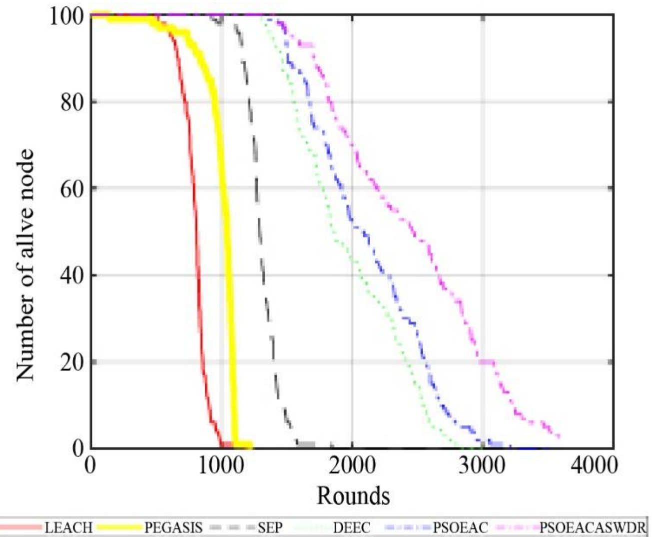


Fig. 3 Variation in the number of alive nodes with respect to the number of rounds for different IoT network routing protocols under the WSN environment

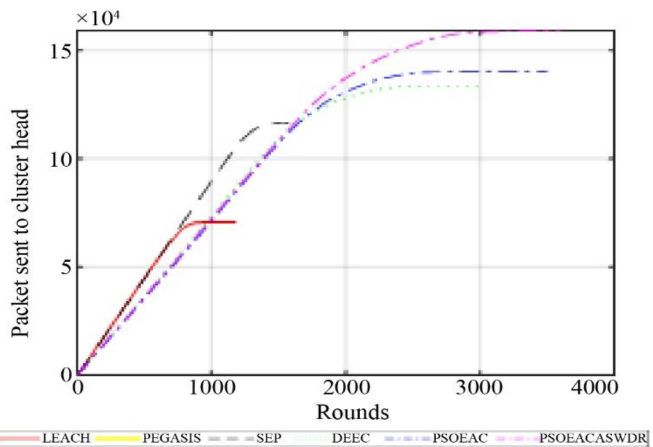


Fig. 4 Number of packets sent to CH with respect to the number of rounds for different IoT network routing protocols under the WSN environment

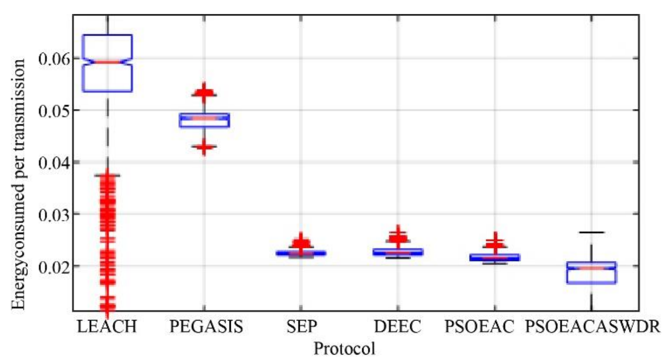


Fig. 5 Distribution of energy consumed per transmission while running a simulation for different IoT network routing protocols under a WSN environment

The network simulation parameters are considered for a packet size of 4000 bytes, a field area of 100x100m2, and 100 sensor nodes with standard WSN radio model values of energy losses at data transmission/receiving, data aggregation, and path losses (free space or multipath loss). The packet transmission runs for several rounds until all the nodes are dead.

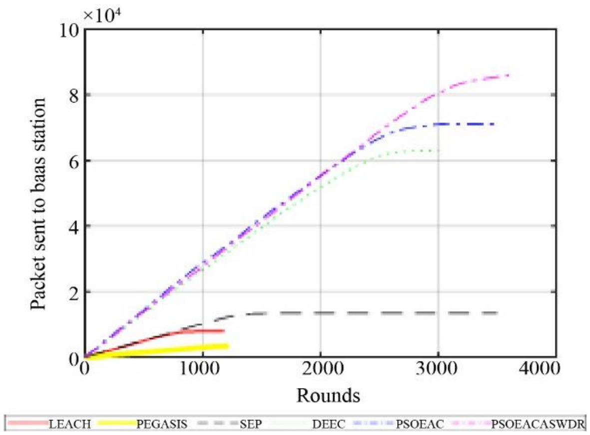


Fig. 6 Number of packets sent to BS with respect to the number of rounds for different IoT network routing protocols under the WSN environment

Key indicators such as the number of active nodes, the volume of packets sent from sensor nodes to the CH, the number of packets transferred from the CH to the BS, and the energy used per transmission are used to evaluate the system performance. The comparative behavior of IoT network routing methods in a WSN environment is illustrated in Figure 6, which shows the fluctuation in the number of packets received at the BS over various rounds. For comparison purposes, simulations of other routing protocols are also executed for conventional and recent standard schemes known as LEACH, PEGASIS, SEP, and DEEC. Figure 3 shows the variation in the number of alive nodes with respect to the number of rounds for different routing protocols. Finally, it is observed that the proposed protocols, i.e., PSOEAC and PSOEACAWWDR, run for a longer number of rounds than the DEEC and SEP.

The conventional method, LEACH, has the lowest lifetime. The higher lifetime allows for more data transmission for packet transmission from node to CH as well as CH to BS, as shown in Figures 4 and 6. Figure 5 shows the energy consumed per transmission. Since energy consumption mainly depends on the distance from source to destination and the number of packets transmitted, the Optimum location of CHs found by PSO helps to minimize the distance, while compression of large data after aggregation at CHs gives a compression ratio of 40% to 50% that further helps to reduce data packet size in order to reduce energy consumption. Figure 5 shows the boxplot where each box bottom and top border indicates maximum and minimum energy, and the central notch shows the average energy consumed. It shows that the proposed protocol gives the minimum average energy consumption. The results shown in plots are further summarized and given in Tables 3 and 4. In Table 2, the performance comparison in terms of statistical values is shown for energy consumed per transmission and total packets sent over the network lifetime. The PSOEACASWDR gives the minimum value of average energy consumed. The highest number of packets is also transmitted under the proposed protocol.

Table 3 gives the value of the round at which the first dead node is observed. Half of the nodes are dead, 90% nodes are dead, or all the nodes are dead (Last Dead). In the proposed protocol, 1st observed at 1404 rounds is known as the stability period, and the last dead, i.e., network lifetime, is 3620 rounds. Table 3 shows the effectiveness of the proposed work in enhancing the lifetime of the network by comparing different protocols (Leach, Pegasis, etc.). The table records the first dead node, half the nodes dead, ninety percent of the nodes dead, and the last dead node (i.e., network lifetime). Conventional protocols such as LEACH perform poorly, with the first node dying at just 508 rounds and the entire network expiring at 1175 rounds. SEP and PEGASIS offer slightly better performance but remain limited in stability and longevity. DEEC improves further, with the first dead node at 1307 rounds and the network surviving until 2811 rounds. However, the proposed PSOEACASWDR surpasses all, delaying the round respective to the 1st dead node to 1404 rounds and extending the respective round of the last dead node to 3620 rounds, indicating a substantial enhancement in both stability period and overall lifetime.

Table 2. Statistical analysis of energy consumption and packet transmission under different IoT network routing protocols in WSN environment

		LEACH	**PEGASIS**	**SEP**	**DEEC**	**PSOEAC**	**PSOEAC ASWDR**
Energy Consumed per Transmission (Joules)	Maximum	0.1208	0.0538	0.0251	0.0264	0.025	0.0265
	Minimum	0.0033	0.0426	0.0217	0.0215	0.0206	0.0035
	Average	0.0555	0.0484	0.0225	0.0228	0.0217	0.0182
	Std. Dev.	0.0178	0.0025	0.0005	0.0009	0.0009	0.0037
	Variance	3.1×10^{-4}	6.1×10^{-6}	2.8×10^{-7}	7.7×10^{-7}	7.5×10^{-7}	1.3×10^{-5}
Total Packets sent	Node to CH	70670	Not Applicable	116400	133600	140200	159100
	CH to BS	7914	3378	13420	62930	71180	85790

Table 3. Performance analysis of network lifetime

	1st Dead	Half Dead	90% Dead	Last Dead
LEACH	508	807	903	1175
SEP	924	1289	1462	1842
PEGASIS	141	1039	1092	1216
DEEC	1307	1860	2550	2811
PSOEAC	1348	2091	2698	3226
PSOEACASWDR	1404	2471	3206	3620

Table 4. Comparison of the performance of the proposed work, PSOEACASWDR, with recent methods

Comparison to recent methods in terms of compression ratio				Comparison to recent methods in terms of average energy consumption.		
Method	Author (Year)	CR		Method	Author	Avg. energy consumption
Block-based Haar Wavelet transforms and COVIDOA[29]	Khafaga et.al (2023)	25.6%		PRVD [32]	Elyyan et.al. (2023)	.021
Tchebichef moments and ABC[31]	Hosny et.al (2018)	19%		EGRPM [27]	Naghibi et.al (2020)	.285
Hahn Moments and ABC [30]	Bencherqui et.al (2022)	15.5%		RRP [28]	Zomaya et.al. (2017)	.315
PSOEACASWDR	(Proposed)	42%		PSOEACASWDR	(Proposed)	.018
*ABC: Artificial bee colony						

3.1. Role of ASWDR

After aggregation at each CH, the combined data packets are compressed using ASWDR before being sent to the BS. The compression reduces packet size by about 40–50%, as mentioned in the results. Smaller packets mean less transmission energy. It also reduces bandwidth usage, enabling the network to handle more nodes or more frequent transmissions. ASWDR compresses aggregated data, minimizing communication cost. Finally, the compressed packets are transmitted to the BS through DEEC-based routing. Simulation results show that ASWDR helps lower the average energy per transmission to 0.018 J. The network lifetime extended to 3620 rounds, compared to 2811 for DEEC and only 1175 for LEACH. The compression ratio achieved (~42%) is significantly higher than prior works (15-25%). In this article, ASWDR is not used in isolation but as a compression layer embedded inside the routing protocol.

It tackles issues of high transmission cost by reducing transmitted data volume, thereby saving energy and improving efficiency. Table 4 is given here for the validation of the proposed work by comparing with the performance results of recent methods published in the latest work under the IoT application domain of data compression and routing. The novelty of the proposed work is obvious in that none of the literature has combined optimization and data compression for enhancing IoT system applications in a WSN environment. In terms of data compression methods in IoT framework comparisons are shown with Khafaga et. al, Hosny et.al, and Bencherqui et.al in terms of Compression Ratio (CR) in percentage. It may be observed that the CR of the proposed work using ASWDR is approximately 42% while other methods only have CR between 15% and 25%. Similarly, the comparison is made to the literature that has applied energy-efficient data transmission techniques. Energy-Efficient Geographic Routing Protocol (EGRPM), Rendezvous-based Routing Protocol (RRP), and PRVD are other protocols that are considered here. The proposed work shows minimum average energy consumption compared to other methods.

Similarly, for energy efficiency, the proposed protocol again demonstrates superiority, consuming only 0.018 Joules on average. This is lower than Elyyan et al. (2023) with 0.021 Joules, and significantly less than Naghibi et al. (2020) and Zomaya et al. (2017), which recorded average consumption of 0.285 and 0.315 Joules.

3.2. Novelty

The proposed work is novel in terms of the unique integration of PSO for Cluster Head (CH) selection with ASWDR data compression, which is applied within the DEEC framework. Previous studies have largely focused on optimizing clustering strategies or employing compression methods like Haar transforms, Hahn moments, or Tchebichef moments. However, none have attempted to combine optimization and compression simultaneously. By doing so, this work introduces a holistic approach that minimizes the consumption of energy not only by selecting the highly efficient set of CHs for routing but also by reducing the volume of data transmitted through efficient compression. The significant improvement over conventional protocols includes a compression ratio of about 42% and extends network lifetime.

4. Conclusion

In order to improve the lifespan and functionality of WSN, an energy-efficient routing protocol using PSO has been developed. By choosing the most energy-efficient option among a number of possible combinations of fittest nodes, such as CH, this method prolongs the network's lifetime. By examining the location, distance, residual energy-based advanced parameters of clusters and CH, PSO is used to assess and choose the best set of CH ids. One ideal combination of best-fit nodes is chosen from the group of possible CHs for the reduction of the network's overall consumption of energy. Additionally, packet size is reduced by using ASWDR data compression to use less energy during the communication process from CH to BS the suggested PSOEACASWDR greatly enhances WSN-enabled IoT applications. Additional Quality of Service (QoS) factors, such as normalized routing load, higher throughput, and decreased packet loss, have improved as a result of this method's deployment. Simulation findings show that the proposed work is not only effective, but it also greatly increases the operational lifetime of WSN. Furthermore, a comparison analysis shows that PSOEACASWDR outperforms existing protocols like DEEC, SEP, etc., in terms of overall performance.

Finally, routing schemes have been shown to be trustworthy options for allowing real-time and dependable IoT applications with guaranteed QoS. Further research might be needed to combine PSO with current routing approaches to address large-scale routing difficulties in hybrid sensor network systems.

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