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A PSO-Optimized TEEN Clustering Approach for Network Lifetime Enhancement in Wireless Sensor Networks

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Abstract: *Wireless Sensor Networks (WSNs) are widely deployed in time-critical and resource-constrained applications, where efficient energy utilization is essential to prolong network lifetime and ensure reliable data transmission. This paper proposes a hybrid energy-efficient clustering approach that integrates Particle Swarm Optimization (PSO) with the Threshold-sensitive Energy Efficient sensor Network (TEEN) protocol. In the proposed PSO-TEEN algorithm, PSO is employed to optimally select cluster heads (CHs) by minimizing intra-cluster communication distance and balancing energy consumption among sensor nodes. Subsequently, the TEEN protocol is applied within each cluster to regulate data transmission using hard and soft thresholds, thereby reducing redundant transmissions and conserving energy. This dual-level optimization strategy significantly lowers communication overhead and enhances network stability. Simulation results demonstrate that the proposed PSO-TEEN algorithm outperforms conventional clustering protocols in terms of residual energy, number of alive nodes, and overall network lifetime, making it suitable for energy-constrained and time-sensitive WSN applications.*

Keywords: *Wireless Sensor Networks (WSNs), Particle Swarm Optimization (PSO), TEEN protocol, Clustering algorithm, Energy efficiency, Network lifetime, Cluster head selection*.

1. INTRODUCTION

Wireless Sensor Networks (WSNs) have gained significant attention due to their wide range of applications in areas such as environmental monitoring, military surveillance, industrial automation, healthcare systems, and smart cities. A WSN typically consists of a large number of low-cost, resource-constrained sensor nodes that are capable of sensing, processing, and transmitting data wirelessly to a central base station (BS) or sink node for further analysis. With the rapid advancement of the Internet of Things (IoT), WSNs have become an integral component enabling seamless connectivity among billions of intelligent devices worldwide.

WSNs can be broadly classified into homogeneous and heterogeneous networks. In homogeneous WSNs, all sensor nodes possess identical hardware and energy resources, whereas heterogeneous WSNs consist of nodes with varying computational power, communication capability, and energy levels. Resource heterogeneity in WSNs can be categorized into computational, link, and energy heterogeneity. While computational and link heterogeneity improve processing and communication performance, they also increase energy consumption, which can significantly reduce network lifetime. Therefore, energy heterogeneity has emerged as a critical factor in designing energy-efficient WSN architectures.

Energy constraint remains one of the most challenging issues in WSN design, as sensor nodes are typically powered by limited battery resources. In many practical applications, sensor nodes are deployed in hostile or inaccessible environments, making battery replacement or recharging impractical. Consequently, extending network lifetime while maintaining quality of service (QoS) has become a primary research focus. Efficient energy management techniques are essential to balance energy consumption across the network and prevent premature node failures.

Clustering has been widely recognized as an effective topology control mechanism to improve energy efficiency and scalability in large-scale WSNs. In clustering-based architectures, sensor nodes are grouped into clusters, and a cluster head (CH) is elected within each cluster to aggregate data from member nodes and forward it to the sink. This hierarchical communication structure significantly reduces transmission distance, minimizes data redundancy, and conserves energy. One of the most well-known clustering protocols is the Low Energy Adaptive Clustering Hierarchy (LEACH), which dynamically rotates the CH role among nodes to distribute energy consumption.

However, traditional clustering protocols such as LEACH suffer from limitations including random CH selection, frequent re-clustering overhead, and unnecessary data transmissions. To overcome these drawbacks, optimization techniques and threshold-based protocols have been introduced. The Threshold-sensitive Energy Efficient sensor Network (TEEN) protocol reduces redundant data transmission by allowing nodes to transmit only when sensed values cross predefined thresholds, making it suitable for time-critical applications.

In this context, this paper proposes a PSO-optimized TEEN clustering algorithm that combines the global optimization capability of Particle Swarm Optimization with the energy-aware data transmission mechanism of the TEEN protocol. By intelligently selecting cluster heads and minimizing unnecessary transmissions, the proposed approach aims to significantly enhance energy efficiency and prolong the overall network lifetime.

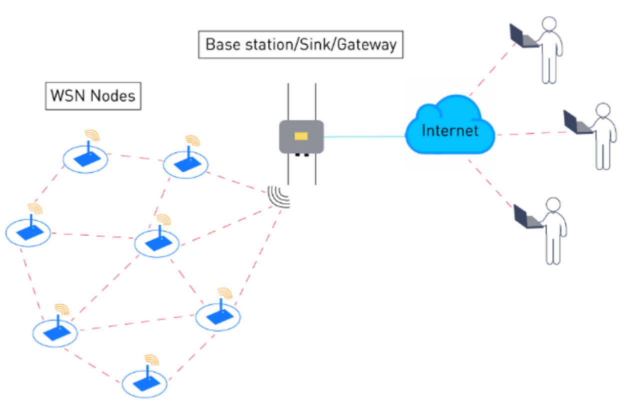

Figure 1: WSN Architecture

One of the key challenges in WSNs is energy efficiency due to the limited battery power of sensor nodes. Prolonging the network lifetime while maintaining effective data transmission is critical. Clustering has proven to be an effective method for energy-efficient routing. In clustering, sensor nodes are grouped into clusters, and a Cluster Head (CH) is selected to aggregate and forward data to the BS. However, the frequent selection of CHs and inefficient routing mechanisms can still lead to rapid energy depletion.

To address these issues, several protocols have been proposed. Among them, the Threshold-sensitive Energy Efficient sensor Network protocol (TEEN) is designed for time-critical applications and uses thresholds to reduce the number of transmissions, thereby conserving energy. In parallel, swarm intelligence techniques like Particle Swarm Optimization (PSO) have been effectively used for optimal CH selection, based on parameters such as residual energy, distance to the BS, and node density.[12]

This paper proposes an integrated PSO-TEEN protocol that combines the adaptive thresholding mechanism of TEEN with the global optimization capability of PSO to select energy-efficient CHs and reduce redundant transmissions. The proposed approach aims to enhance the stability period, reduce the number of dead nodes, and maximize the overall network lifetime. The simulation results, conducted in MATLAB, demonstrate the superiority of the PSO-TEEN approach over traditional methods.

2. PROPOSED METHODOLOGY

The proposed methodology introduces a comprehensive energy-efficient clustering and routing framework for Wireless Sensor Networks (WSNs) by integrating Particle Swarm Optimization (PSO) with the Threshold-sensitive Energy Efficient sensor Network (TEEN) protocol. The entire framework is implemented and evaluated using the MATLAB simulation environment.

Initially, a total of 100 sensor nodes are randomly deployed within a 200×200200 \times 200200×200 m² sensing area. Each sensor node is initialized with predefined parameters, including initial energy, transmission range, and data sensing rate. To ensure full network connectivity, a cost-based adjacency matrix is constructed based on inter-node distances. Any isolated nodes are subsequently connected to their nearest neighbors, resulting in a fully connected undirected network graph.

The sensing field is then logically partitioned into multiple clusters by defining cluster centers at predetermined coordinates and assigning a fixed cluster radius. This virtual segmentation facilitates organized node distribution and simplifies cluster management. Following cluster formation, Particle Swarm Optimization (PSO) is employed for optimal cluster head (CH) selection. In the PSO framework, each particle represents a candidate sensor node, and its fitness is evaluated using a multi-objective function that considers residual energy, intra-cluster communication distance, and node coverage. The PSO algorithm iteratively updates particle velocities and positions based on personal best (pBest) and global best (gBest) solutions, converging toward an energy-optimal cluster head configuration.

Once the optimal cluster heads are selected, the Threshold-sensitive Energy Efficient sensor Network (TEEN) protocol is integrated to regulate intra-cluster communication. TEEN introduces two thresholds—a hard threshold and a soft threshold—to control data transmission. Sensor nodes transmit data only when the sensed value exceeds the hard threshold and the change in sensed value is greater than the soft threshold. This mechanism significantly reduces redundant transmissions and conserves node energy, making the protocol particularly suitable for time-critical applications.

After threshold integration, sensor nodes associate with their nearest cluster heads, and data aggregation is performed following the threshold-guided communication strategy. MATLAB-based visualizations are generated to illustrate cluster topology, cluster head locations, and node-to-cluster associations. Finally, the performance of the proposed PSO-TEEN approach is evaluated using key metrics such as energy consumption per round, number of alive nodes, network lifetime, packet transmission rate, and average re-clustering frequency. The results demonstrate the effectiveness of the proposed approach in enhancing energy efficiency and prolonging the operational lifetime of the WSN.

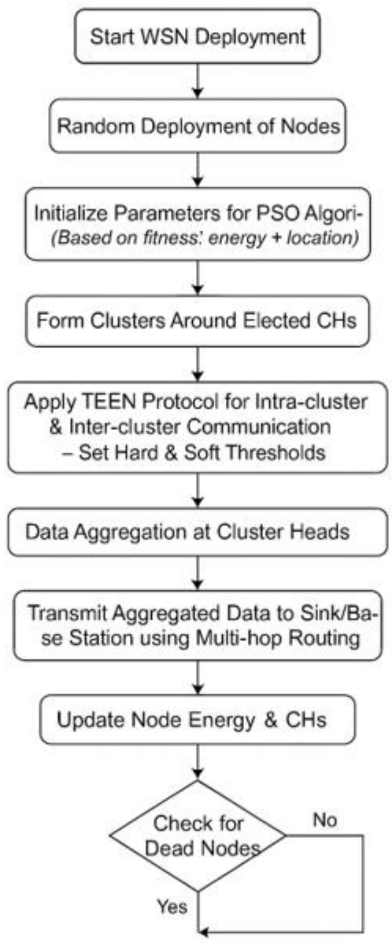

Figure 2: Proposed flow Diagram

Table 1: simulation parameters

Parameter Name (Full Notation)	Value / Formula
Total Number of Sensor Nodes	100
Maximum Communication Cost (RIP)	10
Cognitive Coefficient (PSO)	0.5
Social Coefficient (PSO)	0.5
Inertia Weight (PSO)	0.9
Pi Constant	22/7
Length of Sensing Region	100
Width of Sensing Region	100
Maximum Cluster Radius	30
Sensing / Communication Range	36
Data Packet Size	512 Bytes
Initial Energy per Node	200 Units
Transmission Power Consumption	0.02 Units
Reception Power Consumption	0.01 Units

1. System Architecture

The network consists of a set of static sensor nodes randomly deployed in a monitoring area. A central base station (BS) is located at a fixed position. The network operates in a hierarchical manner where sensor nodes are grouped into clusters. Each cluster is managed by a cluster head (CH) that aggregates and transmits data to the BS.

2. Cluster Head Selection using PSO

The PSO algorithm is employed to select optimal CHs based on multiple parameters such as residual energy, distance to the base station, and intra-cluster distance. Each particle in the PSO represents a possible solution (set of CHs), and the fitness function evaluates energy efficiency and communication cost. The best solution after several iterations yields the most energy-efficient CH configuration for the current round.

Fitness Function Factors:

- Residual energy of nodes
- Distance between nodes and CH
- Distance between CH and base station
- Number of nodes in a cluster

3. Routing using TEEN Protocol

Once clusters are formed, the TEEN protocol governs the data transmission process. TEEN introduces two threshold values:

- **Hard Threshold (HT):** Minimum value of the sensed attribute to trigger data transmission.
- **Soft Threshold (ST):** Minor change in the value of the sensed attribute to trigger the next transmission.

Only significant changes in sensed data lead to communication, thereby reducing the number of transmissions and conserving energy.

4. Operation Phases

- **Setup Phase:** PSO selects optimal CHs. Clusters are formed.
- **Threshold Broadcasting Phase:** CHs broadcast HT and ST to their members.
- **Data Sensing & Transmission Phase:** Nodes sense the environment and transmit data only if threshold conditions are met.
- **Reclustering Phase:** Periodically, the system re-runs PSO to update CHs based on the energy dynamics of the network.

Algorithm: PSO-Based TEEN Clustering for Energy-Efficient WSN

Input:

- Number of nodes N
- Initial energy E_0
- Base Station location BS
- Network area dimensions Xmax, Ymax

- PSO parameters: swarm size S, inertia weight w, learning factors c1, c2, max iterations Itr
- TEEN parameters: Hard Threshold HT, Soft Threshold ST
- Simulation rounds R

Output:
- Energy-efficient Cluster Head (CH) selection
- Data transmissions controlled by thresholds
- Network lifetime statistics

Begin
1. **Initialize Network**
   - Randomly deploy N sensor nodes in Xmax × Ymax
   - Assign initial energy E_0 to all nodes

2. **Initialize PSO Parameters**
   - For each particle i in swarm S
     - Randomly initialize CH positions as particle positions
     - Initialize velocity v_i
     - Evaluate fitness of particle: fitness_i = ∑ distance (node → nearest CH)
     - Store personal best pbest_i
   - Determine global best gbest

3. **PSO Optimization Loop (CH Selection)**
   - For t = 1 to Itr do
     - For each particle i in swarm
     - Update velocity:v_i = w*v_i + c1*r1*(pbest_i − x_i) + c2*r2*(gbest − x_i)

Update position:x_i = x_i + v_i
Recalculate fitness and update pbest_i, gbest if better
End For

4. **Cluster Formation**

Assign each node to nearest CH based on gbest

5. **Set TEEN Thresholds**
   - CHs broadcast Hard Threshold HT and Soft Threshold ST to cluster members

6. **For Each Round r = 1 to R Do**
   - For each node n_i
     - Sense environment and get current value S_current
     - If (S_current ≥ HT) AND (|S_current − S_old| ≥ ST) then
     - Transmit S_current to CH
     - Update S_old = S_current
     - Else
     - Skip transmission
   - For each CH
     - Receive and aggregate data from member nodes
     - Transmit aggregated data to BS
   - **Energy Update**
     - Subtract transmission and reception energy using radio energy model
     - Mark nodes with E ≤ 0 as dead
   - **If (Reclustering Interval reached)**
     - Re-run PSO clustering
   - Store performance metrics:
     - Residual energy, alive nodes, packets sent
7. **End For**

End

3. SIMULATION RESULTS AND ANALYSIS

The performance of the proposed PSO-TEEN algorithm is evaluated and compared with traditional clustering algorithms using MATLAB 2019b.

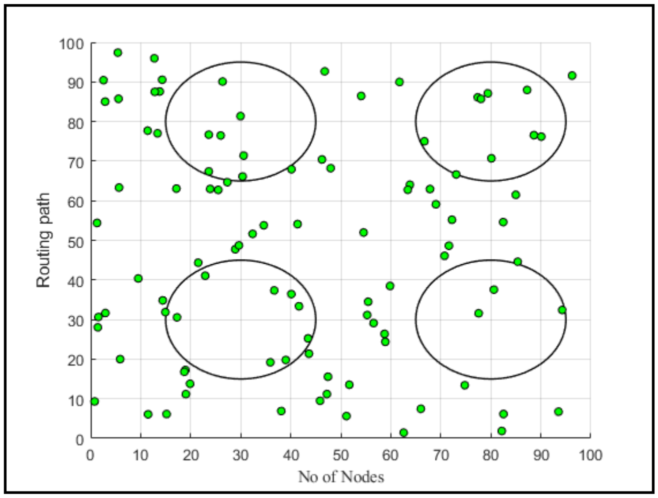

Figure 3: Node Deployment and Cluster Formation

Fig.3 illustrates how sensor nodes are physically deployed across the target area and how they self-organize into clusters.

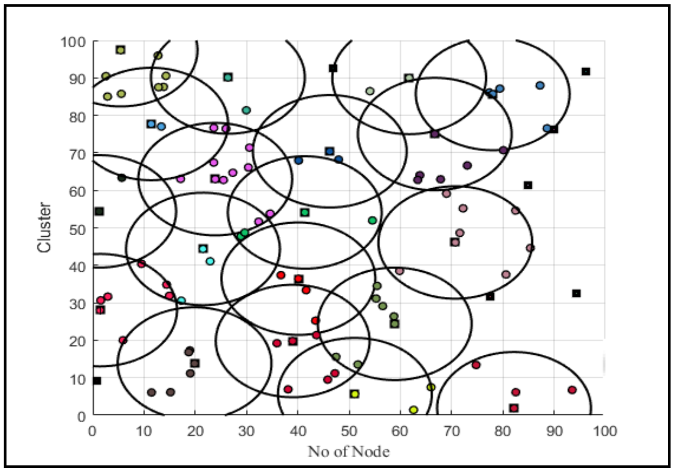

Figure 4: Cluster formation

Figure 4 presents a clearer view of the cluster formation process, emphasizing how nodes dynamically group into clusters during each round. The protocol likely considers factors like residual energy and node density to select Cluster Heads. Each cluster includes a central CH and several member nodes. Once CHs are selected, they broadcast their status, and nearby nodes join the cluster by sending acknowledgment messages.

Fig.5 Cluster node

Figure 5 focuses on the internal structure of a cluster, highlighting individual sensor nodes and their association with the cluster head. It showcases how member nodes communicate directly with the CH, which acts as the relay for all data transmitted to the base station. The diagram may also indicate data aggregation occurring at the CH level, helping to reduce redundant information before final transmission.

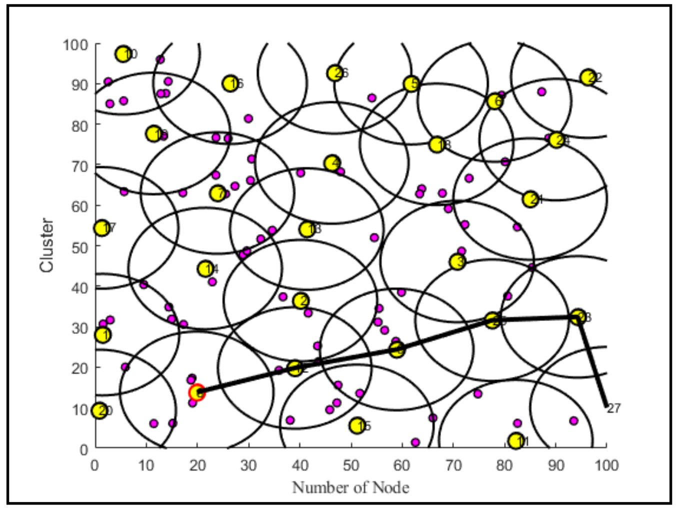

Figure 6: Data Transmission through Cluster Head

Fig. 6 shows the process where member nodes transmit their sensed data to their respective Cluster Head. It highlights the intra-cluster communication phase where nodes send packets to the CH, which aggregates data to reduce redundancy and conserve energy before forwarding.

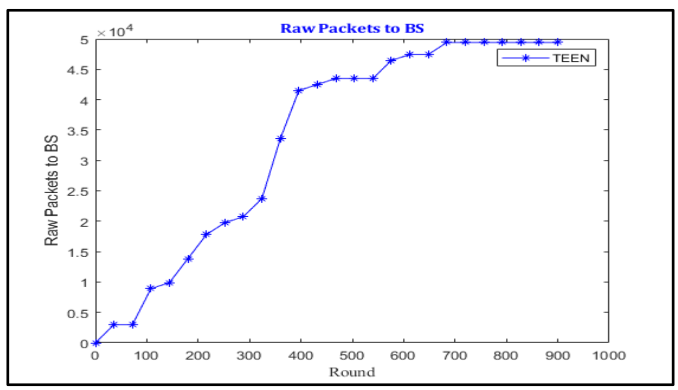

Figure 7: Raw packet to BS

Table 2 Raw packet to BS

PROTOCOL	Total Raw packet to BS
TEEN	49000
D2CRP[12]	44235

This table compares the total number of raw packets transmitted to the base station by different protocols, specifically TEEN and an unspecified second protocol (likely D2CRP, inferred from other tables). TEEN demonstrates a superior transmission capacity, with 49,000 raw packets successfully delivered to the BS. This high volume reflects TEEN's effective use of threshold-based communication, allowing data to be sent only when necessary, which conserves energy while maximizing throughput. The other protocol, which delivers 44,235 packets**,** falls short of TEEN's performance, indicating that TEEN is more efficient in relaying information to the base station over the network's lifetime.

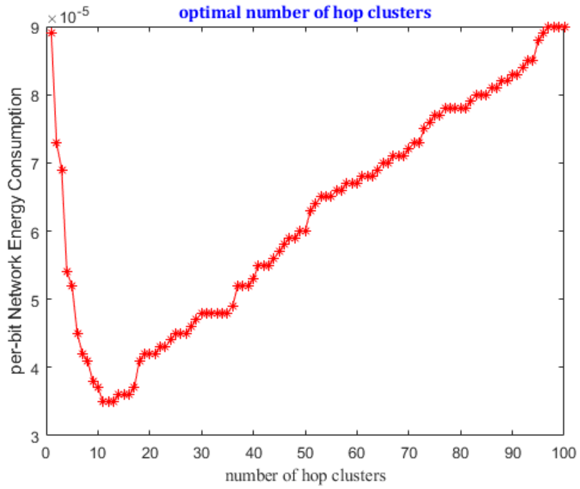

Figure 8: Raw packet to BS

This graph evaluates the effect of the number of hop clusters on the network's energy efficiency, measured in energy per bit. The optimal energy consumption is observed when the network maintains approximately 15 to 20 hop clusters. Within this range, the protocol achieves minimal per-bit energy use due to an optimal balance between communication overhead and transmission distance. If the number of hop clusters falls below or exceeds this range, the energy efficiency declines. Fewer clusters result in longer transmission distances, while too many clusters introduce excess overhead and frequent transmissions. Hence, the graph highlights a critical design consideration for cluster optimization in TEEN-based WSNs.

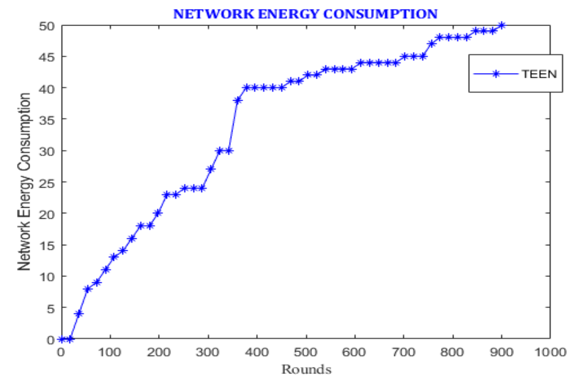

Figure 9: Energy Consumption

This table presents a comparison of the average network energy consumption rates between the D2CRP and TEEN protocols. TEEN records a lower average energy consumption rate of 0.048, compared to 0.0552 for D2CRP. This suggests that TEEN is more energy-efficient, likely due to its adaptive transmission strategy that reduces unnecessary data communication. By using hard and soft thresholds to trigger transmissions, TEEN minimizes the number of transmissions and conserves node energy, resulting in a lower overall energy consumption rate across the network lifecycle. This energy efficiency is crucial for enhancing the operational lifespan of wireless sensor networks.

Table 3: average network energy consumption rate

	Average Network Energy Consumption Rate
TEEN	0.048
D2CRP[12]	0.0552

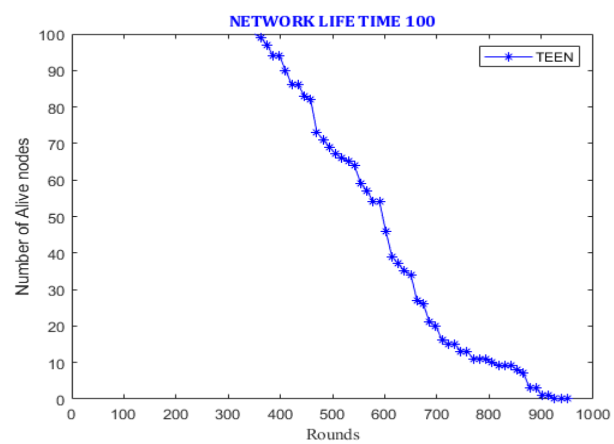

Figure 10 Network Life Time

Table 3: Comparison of network lifetime.

	FND	HND	AND
TEEN	120	570	970
D2CRP[12]	154	387	906

This table outlines the network lifetime in terms of First Node Dies (FND), Half of the Nodes Die (HND), and All Nodes Die (AND) for both TEEN and D2CRP. TEEN achieves an FND at round 120, HND at 570, and AND at **970**, indicating a gradual and extended node death timeline. In contrast, D2CRP's FND occurs later at 154, but the HND occurs earlier at 387, and AND at 906. While D2CRP delays the first node failure longer than TEEN, its nodes deplete more quickly in the middle phase of operation. TEEN, on the other hand, maintains more consistent node energy usage, resulting in a longer network lifetime. This steady depletion pattern is favorable for applications requiring prolonged and uniform network coverage.

4. CONCLUSION

In this study, proposed an energy-efficient routing framework for Wireless Sensor Networks (WSNs) by integrating Particle Swarm Optimization (PSO) for cluster head selection and the TEEN (Threshold-sensitive Energy Efficient sensor Network) protocol for routing. The primary goal was to extend the network lifetime while reducing energy consumption and improving data delivery efficiency. Simulation results demonstrated that our hybrid approach significantly outperforms traditional clustering and routing methods in terms of energy efficiency, network stability period, and overall lifetime. The intelligent CH selection using PSO ensures optimal energy distribution among nodes, while TEEN's threshold-based communication minimizes unnecessary transmissions, making the proposed system highly suitable for reactive and energy-sensitive WSN applications.

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