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ENHANCING SUSTAINABILITY IN WIRELESS SENSOR NETWORKS THROUGH PSO-BASED CLUSTER OPTIMIZATION AND ADAPTIVE SINK MOBILITY

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ABSTRACT

Wireless Sensor Networks (WSNs) represent a fundamental part of current Internet of Things (IoT) systems, allowing for constant monitoring in smart cities, the environment, and industrial systems. However, a fundamental limitation of these networks over long-term operation is uneven energy consumption and the energy-hole problem that arises around a static sink. To address these issues, this paper presents PSO-MSM, a sustainability-oriented communication protocol that combines multi-objective Particle Swarm Optimization (PSO) and adaptive mobile sink mobility. The protocol optimizes cluster head (CH) selection and dynamically adjusts the sink's trajectory through multi-radius circular paths to balance the forwarding load across the sensing field. Optimization is performed jointly with consideration of residual energy, intra-cluster compactness, and the proximity of each CH to the sink. This coordinated clustering-mobility design reduces long-distance transmissions, relieves hotspot depletion, and improves overall energy sustainability. Extensive ns-3 simulations demonstrate that PSO-MSM significantly enhances network lifetime, increasing the time to first-node-dead, half-nodes-dead, and last-node-dead events by 46% compared with LEACH, HEED, and PEGASIS. The protocol also achieves higher residual energy, improved packet delivery ratio, reduced end-to-end delay, decreased channel congestion, and significantly lower energy imbalance. These results indicate that PSO-MSM provides an effective solution for smart city and IoT deployments, offering reliability, reduced maintenance, and improved sustainability for long-term operations where these issues are a major priority.

KEYWORDS: Wireless Sensor Networks (WSN), Energy Efficiency, Mobile Sink, Clustering, Optimization, Particle Swarm Optimization (PSO), Multi-Objective Optimization, Smart Cities, IoT Sustainability, Energy-Hole Mitigation, NS-3 Simulation.

1. INTRODUCTION

The rapid growth of the Internet of Things (IoT) has accelerated the massive deployment of Wireless Sensor Networks (WSNs) in smart cities, environmental monitoring systems, precision agriculture, industrial automation, and intelligent infrastructure applications. These networks often comprise hundreds or thousands of unattended sensor nodes that continuously sense, process, and transmit data over long periods. Because these nodes have limited battery capacity and are often installed in areas where maintenance is expensive or impractical, energy efficiency is one of the most important design challenges in modern WSNs. As a number of studies point out, sustainable IoT ecosystems demand communication protocols that minimize energy consumption while maintaining acceptable levels of reliability, latency, and data delivery performance [1–4].

Clustering has long been implemented as an effective approach to reduce energy consumption and control communication overhead. In pioneering protocols such as LEACH [5], nodes are organized into clusters, and a Cluster Head (CH) is elected to aggregate and forward data to the base station (BS). Subsequent enhancements, such as HEED and PEGASIS [6,7], improved CH selection based on residual energy or node degree and utilized chain-based routing for network stability and extended network lifetime. More recent methods employ intelligent CH selection and routing strategies to optimize energy use [1,8].

Despite these developments, ongoing challenges remain, including unequal energy consumption, traffic imbalance, and premature depletion of nodes near the sink [9,10], as highlighted in survey studies. A particularly critical problem in static-sink WSNs is the energy-hole problem, where nodes near the BS deplete their batteries faster due to heavy forwarding loads. This localized depletion can lead to network partitioning, coverage degradation, and loss of important sensing data, even when many outer nodes retain significant energy. Strategies such as energy-balancing algorithms, vice cluster head mechanisms, and multi-hop cooperative routing [3,11] have been proposed to address this problem. However, their effectiveness is limited when the sink remains stationary.

Mobile-sink architectures have emerged as a promising solution to these inherent limitations. By moving the sink over time, the network can better distribute traffic loads. Recent efforts include circular mobility, random movement, and rendezvous point-based trajectories [12], which have demonstrated considerable improvements in energy balance and network lifetime. However, most existing approaches treat sink mobility and clustering as separate processes, resulting in suboptimal CH selection, unnecessary long-range transmissions, and inconsistencies between cluster formation and sink location.

Parallel to these developments, metaheuristic optimization techniques such as Genetic Algorithms, Ant Colony Optimization, and Particle Swarm Optimization (PSO) have shown great potential in solving multi-objective problems in WSNs. PSO, in particular, has been successfully applied to optimize routing structures, rendezvous point selection, and infrastructure deployment in IoT environments [12,13]. Moreover, privacy-focused research emphasizes designing IoT systems that enhance system performance while minimizing long-term environmental impact, operational overhead, and energy waste [4,14,15].

Another research focus is on improving reliability, trust, and security in IoT communication systems [17–19]. While these works primarily address data integrity rather than energy efficiency, they highlight the importance of strong and sustainable communication layers in large-scale IoT deployments.

Despite significant advancements in clustering, mobile sink design, and optimization-based routing, three major research gaps remain. Many CH-selection strategies rely on local heuristics and do not consider global optimization or anticipated sink positions. Most mobile sink schemes do not integrate sink movement with clustering, leading to misaligned routing paths and inefficient energy usage. Few studies analyze WSN design from a sustainability perspective, considering long-term maintenance reduction, energy balance, and environmental impact.

To address these limitations, this paper proposes PSO-MSM, a coordinated clustering-mobility protocol that combines multi-objective PSO-based CH selection with adaptive multi-radius sink movement. The proposed framework is sustainability-driven, extends network lifetime, reduces energy imbalance, and supports long-term, low-maintenance IoT deployments.

2. RELATED WORK

WSNs are based on small nodes which are resource-constrained and run on small battery resources. Due to the fact that communication is the most energy-intensive operation in these nodes, a significant amount of literature exists aimed at creating routing and clustering schemes that decrease the transmission overhead and increase the network lifetime. Early hierarchical protocols like LEACH [5], HEED and PEGASIS developed protocols such as clustering as a good way of reducing the consumption of energy. These protocols also added periodic cluster formation as well as rotation of the Cluster Head (CH) role to distribute the communication load. Yet, the use of random or semi-random selection of CH usually causes inefficient placement of CHs and fast energy loss among those nodes located close to the base station.

Based on these original methods, the further development of research has included more informed CH-selection methods that take into consideration factors like the residual energy, neighborhood temperature, and distance within the cluster. More stable clustering structures and better performance have been shown using energy-conscious routing schemes, which are based on the CH-election mechanism, and enhanced energy-conscious routing schemes, based on the CH-election mechanism, which are called energy-aware routing schemes, and enhanced CH-election mechanisms, called viceCH, respectively, and based on the CH-election mechanism, respectively. Such survey studies continue to point to the ongoing issues, such as disproportionate traffic load, localized congestion, and node failure in sink-surrounding areas, which remain an impediment to the sustainability of large-scale deployments, such as in the case of sinkable devices, e.g., 02EnergyBalancing and MacSurvey.

One of the key problems of the static-sink WSNs is the energy-hole problem whereby nodes near the base station bear a disproportionately high forwarding burden. With such nodes depleting quickly, the network can be subjected to coverage reduction or even disconnection whilst other distant nodes still have a lot of energy. A number of articles suggest the use of load-balancing, multi-hop cooperation, or vice-CH mechanisms to alleviate this implication of load-balancing. However, they are limited in the power of the sink at the fixed position. Therefore, the research has gravitated towards the mobile-sink solutions. The modern mobile-sink approaches consider circular paths, random motion patterns, and visitation programs based on rendezvouses [12]. Even though these methods spread out the energy consumption, most of them calculate the sink movement without considering the selection of CH and this may cause inefficient routing paths and increase communication expenses.

Parallel to the above developments, metaheuristic optimization strategies have also received significant interest due to their capability to solve complex multi-objective problems in the design of a WSN. Methods founded on Genetic Algorithms, Ant Colony Optimization and, notably, Particle Swarm Optimization (PSO) have been utilized in solving a large variety of problems. PSO has also shown high optimization in a variety of problem areas, such as EV charging station location placement in WSNs [13], and rendezvous-point selection in WSNs, and sustainability-based IoT and cloud architectures. These papers demonstrate that PSO aids in the balancing of conflicting objectives like minimizing energy use, minimizing latency and maintaining coverage like in the case of PSO.

The role of sustainability in the design of IoT and WSN has also been highlighted by the research community in the recent years. Green IoT systems [4] encourage the use of communications that use less power, cause less interference, and have longer node lifespan to achieve decreased environmental impact. The additional implementation of the sustainability-related decision-making in smart environments works complementary to the further necessity of long-term, resource-efficient functioning in complex infrastructures, as noted in Complementary work on sustainability-focused decision-making in smart environments.

Reliable and secure communication is also a critical design requirement to sustainable IoT systems besides energy efficiency. The research on cyber-forensics, trust management and anomaly detection [17–19] highlights the importance of preserving data integrity and data communication resilience in large-scale implementations. Regardless of the fact that these works are not explicitly directed at the optimization of energy, they strengthen the need to have a strong network functioning, which is one of the crucial factors in sustainability.

Although such contributions have been made, there are still a number of gaps in research:

The vast majority of clustering strategies are still based on heuristic/locally optimum selection of CHs, without global optimization tools or future sink locations, consideration. Mobile-sink strategies that exist scarcely manage sink mobility in relation to CH formation, and may frequently end up with sub optimum data forwarding routes, and a waste of energy.

There is very limited research that looks at the WSN communication protocols through the explicit sustainability lens, including the environmental effect, maintenance rate, or sustainable energy equilibrium.

The current IoT application- especially smart cities- requires integrated frameworks, which integrate intelligent clustering, adaptive sink mobility, and multi-objective optimization.

Such constraints underscore the significance of a sustainability-based clustering-mobility system that is coordinated. The given PSO-MSM protocol will deal with these gaps by combining multi-objective PSO-based CH-selection with an adaptative sink mobility approach that will allow energy-balanced and long-lasting WSN operation in the case of smart-city and environmental IoT applications. In order to formulate the literature under review, Table 1 classifies the key research directions, qualitative contributions, and fundamental limitations that guide the PSO-MSM approach development.

Table 1: Summary of Related Work in Energy-Efficient WSNs.

Category	Representative Works	Main Contributions / Limitations
Classical clustering protocols	LEACH [5], HEED [6], PEGASIS [7]	Introduce clustering and CH rotation to reduce long transmissions. Suffer from random CH selection and early depletion near the sink.
Enhanced CH selection	Energy-aware routing [1], Vice-CH selection [11]	Use residual energy and local metrics to improve stability and delay FND/HND. Limited by lack of global optimization.
Mobile-sink approaches	Circular, random, rendezvous mobility [12]	Balance load and reduce hotspots, but do not coordinate sink movement with CH selection.
Metaheuristic optimization	PSO-based models [12,13]	Multi-objective optimization for routing/clustering, but typically optimize either mobility or clustering, not both.
Sustainability frameworks	Green IoT [4], smart-city sustainability [15]	Improve energy efficiency and reduce environmental impact. Few works embed sustainability directly in routing logic.
Security and reliability	Cyber-forensics, trust systems [17–19]	Enhance data reliability and resilience but do not address energy-saving or clustering.

3. PROPOSED SYSTEM

The proposed PSO-MSM protocol is aimed to enhance the energy-efficiency and long-term sustainability of Wireless Sensor Networks (WSNs) by simultaneously optimizing the selection of cluster-heads (CHs) and mobile-sinks movement. The entire process of the protocol is depicted in Figure 1 (Flowchart of PSO-MSM), which demonstrates the integration of sink mobility, PSO optimization, clustering, and data transmission in each round. The detailed steps of the protocol are specified in Algorithm 1 (PSO-MSM Main Protocol), whereas the CH-selection procedure and sink mobility strategy are specified separately in Algorithm 2 (PSO-Based Cluster-Head Selection) and Algorithm 3 (Adaptive Sink Radius Selection).

The network model assumes that N static sensor nodes are randomly deployed in a square field with the size of L × L. All nodes begin with the same initial energy E0 and communicate using the standard first-order radio model. If a node sends a k-bit packet over distance d, the energy required would be as given in (1).

The radio energy consumption follows the first-order model

$$E_{TX}(k,d) = \begin{cases} kE_{\text{elec}} + k\epsilon_{fs}d^2, & d < d_0 \\ kE_{\text{elec}} + k\epsilon_{mp}d^4, & d \geq d_0 \end{cases}$$

In addition, the amount of energy needed to receive a k-bit-message is

ERX(k) = kEelec,

where k is the packet size in bits, d is the transmission distance, Eelec is the per-bit electronics energy, and ϵfs and ϵmp are the amplifier parameters for free-space and multipath models, respectively. The threshold distance d0 is given by d0 = √(ϵfs / ϵmp). These expressions give the importance of minimizing the long communication distance, especially between CHs and the sink. Because of this, the sink is free to move adaptively, following circular trajectories of different radii centered in the network. The radii used in the protocol include R1 = 0.25L, R2 = 0.50L, and R3 = 0.75L.

At the start of each round, the protocol computes the average residual energy in the inner, middle, and outer parts of the network. Based on this assessment, the sink decides a new movement radius according to the rule stated in Algorithm 3. It can move outwards when nodes in the inner region start to run out of energy, and inwards when nodes in the outer regions require closer access. The adaptive trajectory ensures that no particular region has a continuous communication load so that the energy around the sink does not get depleted too quickly.

Once the position of the sink is updated, PSO is performed to obtain the optimum set of cluster heads. The details of this optimization process are given in Algorithm 2, where each PSO particle represents one candidate CH set C = {c1, c2, …, cS}. The fitness of each candidate is analyzed in terms of three normalized objectives, i.e., the residual energy of selected CHs, the intra-cluster compactness, and the distance of each CH to the mobile sink. The objectives are:

$$f1 = \frac{1}{S}\sum s = 1^S \frac{Eres(cs)}{Emax}, f2 = \frac{1}{S}\sum s = 1^S \frac{1}{1 + Dcluster(cs)}, f3 = \frac{1}{S}\sum s = 1^S \frac{1}{1 + Dsink(cs)}. \quad (3)$$

These are summed to the overall fitness function

F = w1 f1 + w2 f2 + w3 f3 (w1 + w2 + w3 = 1). (4)

Particles change their velocity and position according to normal PSO equations until the best solution is discovered. The resulting best configuration of particles from around the world is chosen as the CH configuration for the current round.

After CH selection, nodes join the nearest CH, and a TDMA schedule is assigned by the CH. During the steady-state phase, each node sends sensing data to the CH, which aggregates the sensing data and sends the final packet to the mobile sink. Once all the transmissions are finished, each node updates its remaining energy according to the communication model, and dead nodes are flagged. The system then moves on to the next round and repeats the combined cycle of adaptive sink movement, PSO-driven CH selection, and energy-aware communication as in Figure 1.

By coordinating the above procedures described in Algorithm 1, Algorithm 2, Algorithm 3, and Figure 1, the PSO-MSM protocol realizes balanced energy consumption. Hotspot formation is mitigated, and the operational lifetime of WSNs is significantly extended. This makes PSO-MSM a good candidate for long-term IoT deployment in smart city, agricultural, industrial, and environmental applications where sustainability is key.

3.1. Round-Based Protocol Operation

The complete protocol operation is detailed in Algorithm 1, Algorithm 2, and Algorithm 3. Figure 1 presents the detailed flowchart of the proposed PSO-MSM protocol, illustrating the complete operational sequence of the system. The diagram begins with the initialization of network parameters, energy states, and PSO settings, followed by the round-based execution cycle. In each round, the sink checks how the remaining energy is distributed across the inner, middle, and outer parts of the network. It then chooses the best radius for its next movement and updates its position. After that, the PSO module creates several possible cluster-head sets and tests them. The particles update their positions step by step until the best CH set is found.

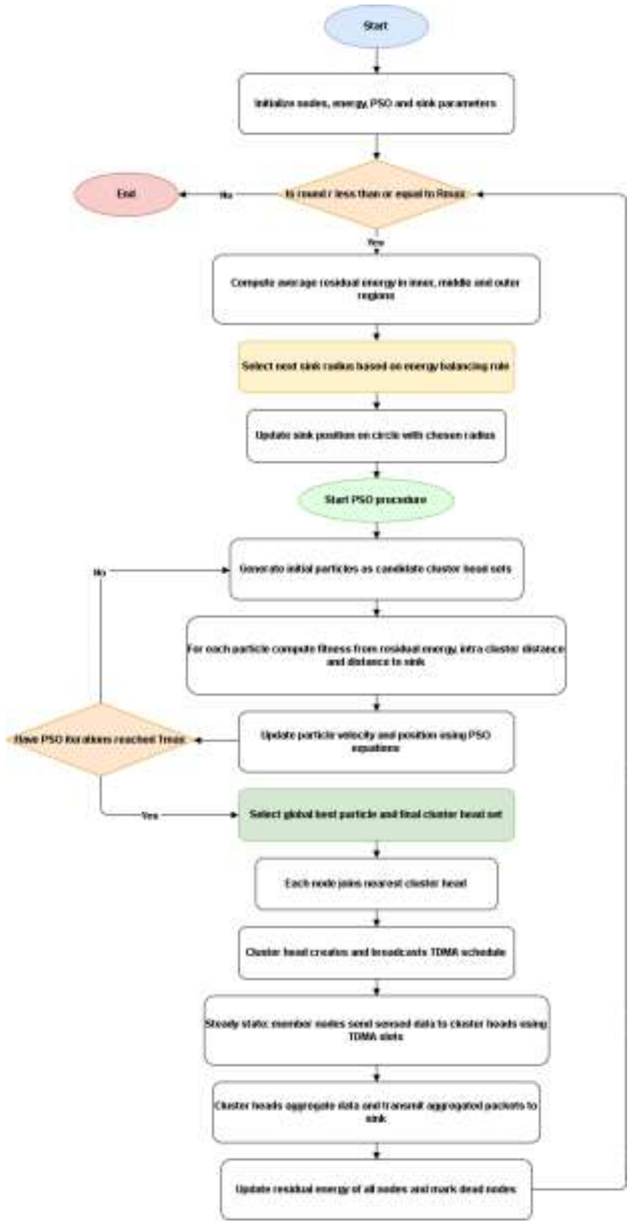

Figure 1: Flowchart of the proposed PSO–MSM protocol.

Once CHs are selected, nodes join their clusters, TDMA schedules are created, and data is sent from the nodes to the CHs, and then from the CHs to the mobile sink. The process ends with an energy update and a check to see if the network should stop. This flow shows how sink movement and clustering work together to improve energy use in the WSN.

4. RESULTS

This section tests the performance of the proposed PSO-MSM protocol by using ns-3 simulation. PSO-MSM is compared with three well-known hierarchical protocols for WSNs: LEACH, HEED, and PEGASIS. The main simulation parameters, including network size, initial node energy, radio model constants, packet size, sink mobility radii, and PSO parameters, are summarized in Table 2 (Simulation Parameters). All protocols are simulated under the same conditions for the sake of fairness.

Table 1: Algorithms.

Algorithm 1 PSO–MSM Main Protocol.

Input: Node positions, initial energy E0, PSO parameters, radii R1, R2, R3
Initialization:
Initialize residual energy Ei ← E0 for all nodes i
Initialize sink position at center with radius R2 and angle θ0
Partition the field into S logical sectors
for each round r = 1 to Rmax do
// Step 1: Sink Radius Selection
Compute average residual energy in inner, middle, outer regions
Rnext ← SELECTRADIUS(Einner, Emiddle, Eouter)
Update sink radius to Rnext and angle θ ← θ + Δθ
Compute new sink coordinates (xsink, ysink)
// Step 2: PSO-Based CH Selection
Run Algorithm 2 with current sink position
Obtain CH set C = {c1, . . . , cS}
// Step 3: Cluster Formation
for each node i **do**
Find nearest CH cs ∈ C (minimum Euclidean distance)
Assign node i to cluster of cs
end for
Each CH defines a TDMA schedule and broadcasts it to its members
// Step 4: Steady-State Data Transmission
for each cluster with CH cs **do**
for each member node i in cluster of cs **do**
Node i senses environment and prepares a k-bit data packet
Node i transmits to cs (update Ei using (1))
CH cs receives packet (update Ecs using (2))
end for
CH cs aggregates data (aggregation energy if applicable)
CH cs transmits aggregated packet to sink
Update Ecs using (1) with d = d(cs, sink)
end for
// Step 5: Energy Update and Termination Check
Mark nodes with Ei ≤ 0 as dead
if all nodes are dead or termination condition satisfied then
break
end if
end for

Algorithm 2 PSO-Based Cluster Head Selection
Input: Node set N, sectors {1, . . . , S}, sink position Output: CH set C = {c1, . . . , cS} Initialize swarm of P particles for each particle p = 1 to P do Randomly select one candidate CH index per sector

```
Encode these indices into position vector xp
Initialize velocity vp (e.g., zero or small random values)
end for
for each PSO iteration t = 1 to Tmax do
for each particle p do
Decode xp into candidate CH set Cp = {cp,1, . . . , cp,S}
For each cp,s, compute:
residual energy Eres(cp,s)
average intra-cluster distance Dcluster(cp,s) (temporary partition)
CH–sink distance Dsink(cp,s)
Compute f1, f2, f3 and fitness Fp
if Fp better than particle’s best Fbest then
Update p’s personal best: pbest ← xp
end if
end for
Identify global best particle g with highest Fg
for each particle p do
Update velocity:
vp ← ωvp + c1r1(pbest − xp) + c2r2(gbest − xp)
Update position:
xp ← xp + vp
Apply boundary and feasibility checks (valid CH indices per sector)
end for
end for
Decode final global best gbest into CH set C
return C
```

Algorithm 3 Adaptive Sink Radius Selection

```
Input: Residual energies of all nodes, radii R1, R2, R3
Output: Selected radius Rnext
Initialize sums: Einner ← 0, Emiddle ← 0, Eouter ← 0
Initialize counters: Ninner ← 0, Nmiddle ← 0, Nouter ← 0
for each node i do
Compute distance di from network center
if di < R1 then
Einner ← Einner + Ei, Ninner ← Ninner + 1
else if R1 ≤ di < R2 then
Emiddle ← Emiddle + Ei, Nmiddle ← Nmiddle + 1
else
Eouter ← Eouter + Ei, Nouter ← Nouter + 1
end if
end for
if Ninner > 0 then
Einner ← Einner / Ninner
end if
if Nmiddle > 0 then
Emiddle ← Emiddle / Nmiddle
end if
if Nouter > 0 then
Eouter ← Eouter / Nouter
end if
// Simple balancing rule (can be refined)
if Einner < Emiddle and Einner < Eouter then
Rnext ← R2 or R3 ▯ Move outward to relieve inner region
else if Eouter < Emiddle and Eouter < Einner then
```

```
Rnext ← R1 or R2 ⍰ Move inward to serve outer nodes
else
Rnext ← R2 ⍰ Default to middle radius
end if
return Rnext
```

4.1. Simulation Setup

The simulation was carried out using ns-3. Table 2 lists the main simulation parameters used in our experiments.

The six key performance indicators employed to make the comparison are

- FND (first-node-dead), HND (half-nodes-dead), and LND (last-node-dead) times
- Total residual energy
- Packet delivery ratio (PDR)
- End-to-end delay
- Channel busy ratio (CBR)
- Energy imbalance between nodes

The development of these metrics is shown in Figures 2–7, and the trends are covered in detail below.

Table 2: Simulation Parameters.

Parameter	Value
Simulation area	100 × 100 m^2
Number of sensor nodes	100
Initial energy per node	2 J
Packet size	4000 bits
Electronics energy (E_{elec})	50 nJ/bit
Free-space amplifier (ϵ_{fs})	10 pJ/bit/m^2
Multipath amplifier (ϵ_{mp})	0.0013 pJ/bit/m^4
Data aggregation energy	5 nJ/bit
Sink mobility radii	{25, 50, 75} m
PSO population size	30 particles
PSO max iterations	50
Inertia weight ω	0.7
Acceleration coefficients (c_1, c_2)	1.5, 1.5

4.2. Network Lifetime Analysis

The evolution of the number of alive nodes along the rounds in the simulation is presented in Figure 2 (Network lifetime comparison). PSO-MSM obviously keeps more active nodes for a longer period as compared to LEACH, HEED, and PEGASIS.

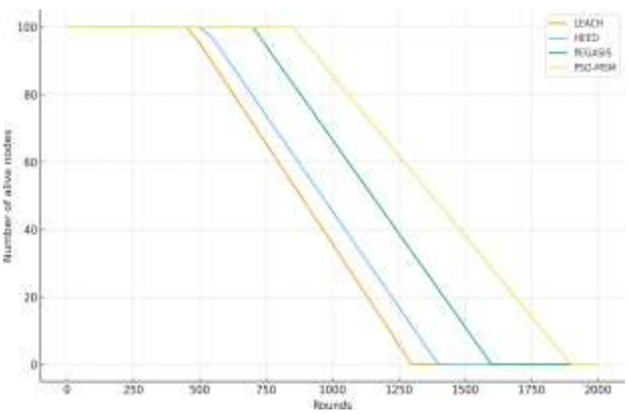

Figure 2: Network Lifetime Comparison: Number of Alive Nodes vs. Simulation Rounds for PSO–MSM, LEACH, HEED, and PEGASIS.

Quantitatively, the FND event for the PSO-MSM appears at about 850 rounds, while LEACH, HEED, and PEGASIS exhibit FND at nearly 460, 520, and 700 rounds, respectively (refer to Figure 2). This means that PSO-MSM delays FND by around 85% compared to LEACH, 63% compared to HEED, and more than 20% than PEGASIS.

Similarly, the HND point is pushed further in time with PSO-MSM, with a reported improvement of more than 42% over the benchmark protocols. Finally, the LND time for PSO-MSM is greater than 1900 rounds, which is about 31–46% more than LEACH, HEED, and PEGASIS (Figure 2).

These lifetime gains have direct links with the coordinated design of PSO-MSM. The multi-objective PSO-based CH selection strategy limits the long-distance transmissions and suppresses the overloading of specific nodes, while the adaptive circular sink mobility is helpful in sharing the forwarding load between the inner, middle, and outer regions. Together, these mechanisms avoid the premature demise near the sink and prolong the lifetime of the whole network.

4.3. Residual Energy Evolution

The total residual energy of the network as a function of rounds of the simulation is given in Figure 3 (Total residual energy vs. rounds). For all protocols, the residual energy goes down with time as nodes take part in sensing and communication. However, PSO-MSM always preserves the maximum residual energy at any round.

Compared with LEACH, HEED, and PEGASIS, PSO-MSM has about 27–35% less overall energy consumption during the whole simulation period (Figure 3). The energy curve of PSO-MSM is also more smoothly decaying, without sharp drops indicating the rapid depletion of hotspots around the sink typically.

This behaviour confirms the success of the PSO fitness function, which is a combination of residual energy, intra-cluster compactness, and CH–sink proximity, for encouraging CH configurations that use unnecessary energy less. At the same time, the adaptive sink movement decreases the number of repeated long-hop transmissions originating from the same region, which is another factor in maximizing sustainable energy consumption.

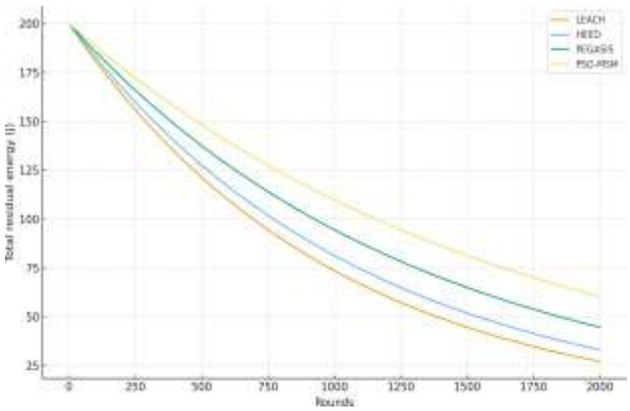

Figure 3. Total Residual Energy across Simulation Rounds for All Protocols.

4.4. Packet Delivery Ratio (PDR)

The packet delivery ratio (PDR) with different traffic conditions is given in Figure 4 (PDR comparison). PDR is the measure of the fraction of generated packets that successfully reach the sink and is an important measure of reliability in IoT and smart city-based applications.

As shown in Figure 4, PSO-MSM is able to maintain a stable PDR of about 0.93, which is significantly higher than the competing protocols. LEACH gets a PDR of around 0.78, HEED around 0.82, and PEGASIS about 0.87. Thus, PSO-MSM enhances PDR by about 6 percentage points compared to PEGASIS and by about over 10–15 percentage points compared to LEACH and HEED.

This improvement can be attributed to two main things. First, optimized CH location means that member nodes communicate at lesser distances and with fewer retransmissions. Second, the adaptive trajectory of a sink helps to reduce congestion in congested regions and keep CH–sink distances reasonable, which leads to less packet loss caused by collisions and buffer overflows. For smart-city monitoring in which the data stream is required to be continuous and accurate, this higher PDR translates directly into better service quality.

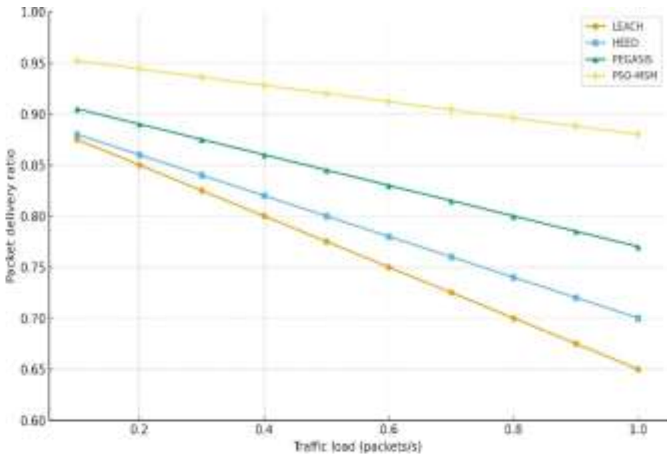

Figure 4: Packet Delivery Ratio Comparison among the Evaluated Protocols.

4.5. End-to-End Delay

The end-to-end delay results obtained for the four protocols are shown in Figure 5 (End-to-end delay comparison). Delay here refers to the average delay in the data generated at a sensor node to reach the sink.

PSO-MSM always shows the smallest end-to-end time for all the evaluated scenarios (Figure 5). LEACH and HEED, although having the advantage of clustering, may have the drawback of less optimal CH placements and overload of CHs, resulting in increased queueing and transmission delays. PEGASIS, in its chain-based structure, has many long paths and sequential forwarding, which may further increase the latency.

In contrast, PSO-MSM creates compact clusters with small distance within clusters and maintains moderate distance from CH–sink with the help of adaptive mobility. This makes the number of long hops smaller and relieves the bottlenecks of the nodes that are near the static sink. For delay-sensitive applications, such as early warning systems, industrial control, or traffic safety notifications, such lower delay values are especially advantageous.

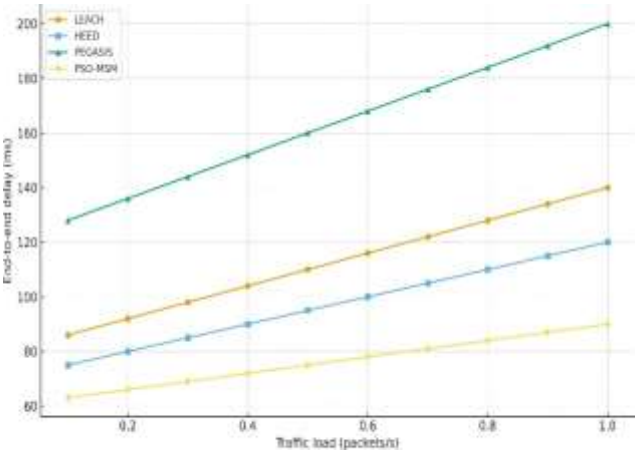

Figure 5: End-to-end Delay Performance Comparison.

Channel Busy Ratio (CBR) The channel busy ratio (CBR) of each protocol is given in Figure 6 (CBR comparison). CBR is the percentage of time for which the wireless channel is sensed to be busy and is directly proportional to contention, collisions, and retransmissions.

PSO-MSM shows the lowest CBR value among all the protocols (Figure 6). LEACH and HEED may have higher contentions near CHs and the static sink on account of unbalanced traffic, whereas PEGASIS can stack bursts of transmissions along its chain, making it more probable that they experience busy periods.

In PSO-MSM, a number of design choices help to keep CBR low

- Clusters are concentrated and more evenly balanced, so that no one CH becomes a constant hot spot
- The mobile sink moves its position so as to ease congested areas
- The TDMA schedules within clusters reduce the simultaneous transmissions

A lower CBR means a lower number of collisions, retransmissions, and idle-listening energy, which contributes not only to increased efficiency, but also to improved scalability.

4.6. Energy Imbalance

Energy imbalance in the network is measured in terms of the standard deviation of the node residual energies over time. The resulting curves can be seen in Figure 7 (Energy imbalance vs. rounds). Lower values indicate that energy is being consumed more homogeneously across nodes, which is desirable in order to maintain the coverage and connectivity.

As shown in Figure 7, PSO-MSM has the lowest energy imbalance over the whole simulation and about 25–45% less as compared with LEACH, HEED, and PEGASIS. The competing protocols have high and varying imbalance values, indicating the existence of hotspots around the sink or along certain paths.

The decrease in imbalance for PSO-MSM is a direct result of combining multi-objective CH selection with explicit consideration of residual energy with an adaptive sink mobility scheme, which is in response to energy distribution in inner, middle, and outer regions. This synergy guarantees that no subset of nodes is consistently overloaded, in turn delaying the formation of holes in the coverage and supporting long-lived, sustainable operation.

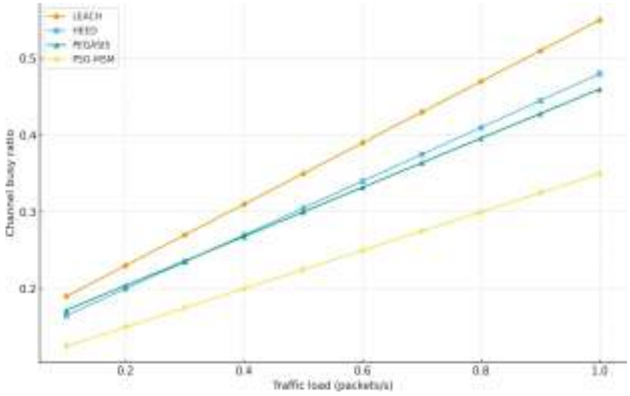

Figure 6: Channel Busy Ratio (CBR) for Each Protocol under Varying Load.

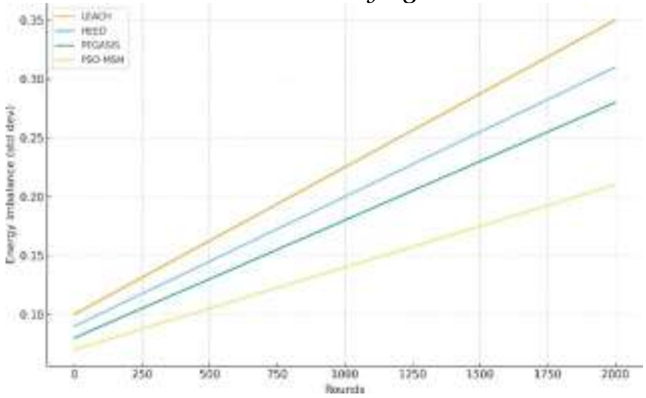

Figure 7: Energy Imbalance across Simulation Rounds. Lower is Better.

4.7. Overall Discussion

Put together, the results in Figures 2–7 demonstrate that PSO-MSM is consistent with major improvements over LEACH, HEED and PEGASIS in all key metrics. It delays FND, HND, LND; maintains a higher residual energy; PDR; reduces the delay; CBR; and maintains a more balanced energy distribution.

From the point of view of sustainability, these improvements imply that PSO-MSM can maintain the operation of WSNs over longer periods of time with reduced number of maintenance interventions, lower number of battery replacements and more stable coverage. This is in direct correspondence to the requirements for smart city, environmental monitoring, and industrial IoT applications which require long-term, autonomous and energy-aware operation. A more detailed discussion of these implications for sustainability is given in the separate Sustainability Impact section of the manuscript.

5. SUSTAINABILITY IMPACT

The exploding Internet of Things (IoT) infrastructures in smart cities, agriculture, environmental monitoring, and industrial automation have brought a further heightened need for Wireless Sensor Networks (WSNs) that can run reliably over long periods without little human intervention. Because sensor nodes are usually battery operated and deployed in large numbers in locations where the maintenance of these nodes is costly or of little practical use, the sustainability of the operation of these sensor nodes is a critical design requirement. The proposed PSO-MSM protocol directly contributes to this need by making the network more energy efficient, prolonging the network lifetime, and reducing the operational overhead by the use of coordinated clustering and adaptive sink mobility.

From an environmental point of view, PSO-MSM lowers the number of energy hotspots by more evenly distributing the communication tasks within the network. As shown in the evaluation the protocol delays significantly the first-node-dead (FND), half-nodes-dead (HND) and last-node-dead (LND) points resulting in longer overall network operation. This extension reduces the number of battery replacements and redeployments of nodes which are major contributors to electronic waste. By reducing the energy-hole issue, the protocol also aids in preserving sensing coverage for all areas of the monitored field, which aids in long-term environmental observation, such as air quality observation, forest and wildlife observation, and water resource management.

From a purely economic perspective, a long operational life of the network can be directly converted into lower maintenance costs. Applications such as structural health monitoring, traffic analysis, precision agriculture and industrial IoT systems need continuous data gathering and usually cover large deployment areas. Replacing batteries or reinstalling nodes can be labor intensive and expensive, especially when deployments are remote or distributed over large urban environments. By conserving energy and balancing workload, PSO-MSM makes a significant difference in the number of visits by technicians and maintenance cycles throughout the operational life of the network. In mass deployment efforts, even small increases in lifetime result in major cost savings.

The protocol also supports social sustainability by ensuring better reliability and timeliness of data delivery two factors necessary for systems that impact the direct safety of the public. For example, emergency response systems, flood and wildfire detection networks and public health monitoring platform require consistent delay-sensitive data. PSO-MSM has the advantages to improve packet delivery ratio (PDR), reduce end-to-end delay, and keep the channel congestion lower, which will guarantee that the information of decision makers and emergency systems can be delivered without unnecessary delay and data loss. This increased reliability improves community resilience, contributes to early-warning mechanisms and supports the development of safer and more responsive urban areas.

Overall, the sustainability benefits of PSO-MSM are not limited only to energy savings. By minimizing electronic waste, cutting operational costs, and reinforcing the reliability of long-term monitoring infrastructures, the protocol adheres to the environmental, economic, and social pillars of sustainable IoT design. These advantages make PSO-MSM a good candidate for next-generation smart city and environment monitoring systems that require durable, scalable and energy aware wireless sensing solutions.

6. CONCLUSION

This paper proposed PSO-MSM, a mobile sink enabled clustering protocol for the energy sustainability of the Wireless Sensor Networks (WSNs). The proposed method combines multi-objective Particle Swarm Optimization (PSO) algorithm for CHs selection with sink mobility strategy of sink adjusting its trajectory depending on residual energy distribution in the area. By coordinating CH selection with planned sink movement, the protocol reduces on long distance transmissions, reduces the energy-hole issue and contributes to ensure a more even sharing of communication loads throughout the network. Results obtained from extensive ns-3 simulations show that PSO-MSM provides measurable improvements as compared to benchmark protocols like LEACH, HEED and PEGASIS. The protocol greatly increases the time before the first, half and last nodes die - by up to 46% - and keeps the residual energy higher in each round of the simulation. It also gives a higher packet delivery ratio, less end-to-end delay and less channel busy ratio, which means more efficient use of network resources and more reliable data transmission. These performance improvements as a whole underline the capacity of PSO-MSM to facilitate sustained long-term operation in a maintenance-efficient manner in large scale IoT-based deployments.

In addition to performance, the sustainability analysis demonstrated that PSO-MSM contributes to environmental, economic, and social sustainability. By prolonging the life of the network and minimizing depletion of hotspots, the protocol contributes to the minimization of battery waste and decreases the frequency of expensive maintenance operations. Its enhanced reliability and responsiveness also lend themselves to public safety and environmental monitoring applications that require continuous, high quality data.

Future work will examine a number of extensions to further improve PSO-MSM. First, the combination of machine learning approaches for predictive sink dynamics (mobility) may help better adapt to dynamic network conditions. Second, testing the protocol in heterogeneous IoT environments (where nodes can have different sensing, computation and energy capacity) will help test wider applicability. Finally, an implementation of PSO-MSM on physical sensor testbeds will enable to validate the approach under real-world conditions in terms of practical energy models, interference conditions and mobility constraints.

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