



Asian Research Association



Hybrid BIRCH-ACO and PSO-MST Strategies for Energy-Aware Data Aggregation in Software-Defined WSNs

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DOI: <https://doi.org/10.54392/irjmt2611>

Received: 19-08-2025; Revised: 20-11-2025; Accepted: 28-11-2025; Published: 10-12-2025



Abstract: In a Wireless Sensor Network (WSN), dozens or hundreds of battery-driven sensors communicate with one another. Batteries have to be replaced frequently when nodes are deployed in unattended environments. Internet of Things (IoT) applications are becoming increasingly scalable and energy-efficient, making energy-efficient data aggregation a critical research focus. As part of this study, two hybrid data aggregation frameworks are presented and evaluated in order to optimize energy consumption and network performance. In the first framework, hierarchical clustering is performed using BIRCH (Balanced Iterative Reduction and Clustering Using Hierarchies), while mobile base station shunting is performed using Ant Colony Optimization (ACO). Using Particle Swarm Optimization (PSO), optimal cluster heads and base stations can be placed, and routing paths can be optimized using the Minimum Spanning Tree (MST) algorithm. Software-defined WSNs reduce computational overhead and improve adaptability by utilizing a software-defined architecture. According to a comparison of energy efficiency, network lifetime, control overhead, and data latency metrics, both approaches outperform traditional static clustering methods significantly; however, the BIRCH and ACO model excels in adaptive clustering and load distribution, while the PSO and MST model provides the best path optimization and the least amount of delay in data transmission.

Keywords: Wireless Sensor Networks, Sensor Nodes, Routing, Clustering, Data Aggregation

1. Introduction

Wireless Sensor Networks (WSNs) are crucial in the development of Internet of Things (IoT), allowing communication and sensing in real-time. Networks like this are made up of spatially autonomous sensor nodes that can detect physical or environment conditions that includes temperature, humidity, vibration and motion. WSNs are an essential component of IoT systems, allowing for data collection, remote monitoring, and intelligent decision-making in domains like as agriculture, healthcare, and smart cities [1, 2]. WSN deployment improves the idea of a linked society by enabling decentralized intelligence, scalability and adaptability.

Despite these advantages, WSNs are mainly energy-constrained since sensor nodes are often battery-powered and located in inaccessible or remote regions, making battery replacement impractical. Communication, mainly data transmission, is perhaps the most-energy intensive task for a sensor node, affecting the network's total lifetime [3]. As a result, energy efficiency has emerged as an important design criterion for system reliability and long-term operation.

Motivated by energy limits, scientists are attempting to establish energy-efficient data collection technologies that reduce redundant transmissions and improve network performance. Data aggregation decreases the quantity of data provided to the base station by aggregating, compression, or combining information received at intermediate nodes, hence saving energy and bandwidth [4]. Cluster-based routing, which groups sensor nodes and pools data at the cluster nodes, has shown promise for boosting network lifetime while assuring accurate and timely information transfer.

The growing interest in the quantum-inspired optimization frameworks for solving the generalized shortest path and knapsack problems, shows how tensor network formulates large-scale optimization [5]. These emerging perspectives reinforce the need for hybrid, and adaptive routing systems capable of integration, optimization, clustering and graph principles.

WSNs mainly rely on the energy efficient routing and clustering protocols to extend the network lifetime. Metaheuristic algorithms are adopted to address these challenges, one of the algorithms used by [6] is the Particle Swarm Optimization (PSO), inspired by social behaviour of fish and swarm. PSO can rapidly converge

towards the optimal solutions in high-dimensional space. Over the period of time, PSO has emerged as one of the most widely used optimization algorithms as they were computationally effective and robustness in dynamic environments. PSO is also employed in wireless communications, energy-aware routing and clustering, while noting the need for hybrid techniques and to improve scalability in networks [7].

The WSN routing systems has shifted towards AI-driven and metaheuristic clustering approaches. These evolutionary models improve the routing efficiency, as many existing protocols lacks the dynamic adaptability and fails to integrate the spatial awareness [8]. PSO model-based data gathering is effective in mobile sink scenarios, providing dynamic cluster head selection and reducing communication overhead [9]. This significant improvements in energy-aware routing in mobile WSNs using PSO has led to a greater impact in the development of hybrid models.

Minimum Spanning Tree (MST) strategies shows potential in reducing redundant links and maintains lightweight routing structures. A dynamic MST maintenance model is capable of updating spanning trees effectively in response to the graph changes, enabling real-time optimization of the network topology [10]. Such dynamic MST approaches can compliment PSO by providing structure-aware topology control during cluster formation and routing process.

Furthermore, conventional clustering techniques are constrained in dynamic settings. Sensor nodes can be distributed throughout a monitoring zone and interact with the BS in an adaptive manner because of their random deployment, low cost, and self-organization features. However, idea drift in streaming data, which is driven by variations in environmental patterns or sensor behaviour, poses a substantial difficulty. Existing concept drift detection approaches typically disregard the underlying local data structures, leading to uncertain outcomes in real-time WSN application [11].

The limits and barriers highlight the importance of adaptive, energy-aware, and concept sensitive data aggregation methods for increasing the efficiency and intelligence of WSN-enabled IoT systems. The rest of the paper is structured as follows: section 2 discusses analogous research endeavours, including the limitations. Section 3 defines the problem statement, while statement 4 discusses the novelty of the research work. Section 5 structures the methodology. Section 6 deals with simulation setup, while section 7 offers the evaluation metrics. Section 8 describes the experimental findings and analysis, while Section 9 concludes the work. Section 10 discuss the limitations of the present work and future scope.

2. Literature Review

This study improves the BIRCH technique for large-scale visual grouping tasks. The m-BIRCH approach clusters high-dimensional data, such as SIFT descriptors and image patches, gradually using a tiny amount of RAM from the dataset. Clusters are updated when new data becomes available. Key features include tools for regulating various density zones in the feature space, as well as data-driven parameter selection to manage summarization granularity. With these advancements, m-BIRCH may now be utilized for online clustering on tough visual datasets like the Hopkins 155 3D motion segmentation dataset [1].

PSO and Minimum Covering Spanning Tree (MCST) algorithm is implemented for mobile data collection in energy efficient WSN network. The proposed technique collects data using two techniques, one is using two SenCars with numerous antennas and the other is using Space Division Numerous Access (SDMA) via the sensor node clusters. The location of the node is calculated using PSO and SenCars route is determined using MCST algorithm. This technique increased the overall network performance, energy usage and reduces latency [2].

The author describes a novel method for combining a BIRCH ensemble with a local structure mapping tool. The suggested method uses a semi-supervised Bayesian framework to evaluate each sample's local similarity and detect concept drift. When a recurring idea is identified, an older BIRCH ensemble classifier is chosen and subsequently improved. If the idea is novel, a BIRCH ensemble classifier is developed and added to the pool. Extensive research on a variety of synthetic and real-world datasets proves the use and superiority of the suggested strategy [3].

An energy-efficient spectrum sensing algorithm is described by the paper for cognitive radio networks using AACDIC. The AACDIC optimizes cluster formation through distributed sensing based on the changing number of primary and secondary users. It achieves faster convergence, reduced sensing errors, and improved detection at low SNR levels (as low as 2 dB). Experiments show a 9.646% reduction in node power consumption and a 24.23% decrease in secondary user energy usage. AACDIC outperforms existing methods in detection accuracy and false positive rates, offering a robust solution for energy-constrained WSN environments [4].

Multimodal optimization aims to find several optima in a search space. While Particle Swarm Optimization (PSO) is widely utilized for this purpose, the effect of communication topologies on niching behavior is little understood. A recent technique incorporates a MST topology, in which particle neighborhoods are determined by MST structures generated throughout each cycle. By removing high-weight edges, the

technique promotes variety while limiting genetic drift. When combined with canonical PSO and Locally Informed PSO (LIPS), this technique exceeds the CEC2013 benchmarks, suggesting its utility in multimodal problem solving [8].

The suggested MST technique efficiently modifies the MST in dynamic weighted undirected graphs without requiring total reconfiguration. It manages structural changes by distinguishing between edges added and removed, and it retains the original MSTs components [11].

CH selection optimization is done using hybrid PSO and improved LEACH architecture [12]. This integration has increased the energy efficiency and network lifetime. In the first stage, Hybrid PSO selects the optimal CH based on the distance between nodes and residual energy consumption. This ensures that there is a balanced distribution of energy consumption across the network. In the second stage, improved LEACH dynamically changes the CH assignments, to save energy and maintain network stability. The proposed technique showed 55% survival rate in nodes and 28% reduction in the average energy consumption [13].

PSO model outperformed ACO due to the faster convergence for wildfire detection. Due to the slower adaptation and effectiveness in deployment tasks, ACO

is used for routing. Overall, PSO is more efficient and reliable method for optimal sensor placement in WSN wildfire monitoring [14]. In resource-constrained IoT contexts, the hybrid routing strategy improves energy efficiency and network lifetime by combining fuzzy clustering and PSO. Fuzzy clustering divides nodes into groups based on their proximity, but an upgraded PSO algorithm chooses the best cluster heads using a fitness function that balances energy usage and distance. MATLAB simulations indicate that this technique outperforms DEEC and LEACH, lowering energy consumption by 52% and 16%, increasing throughput by 112% and 10%, enhancing packet delivery by 83% and 15%, and prolonging network lifetime by 48% and 27% [15].

The authors have developed energy-efficient data collection and routing methods like clustering, adaptive sampling and controlled data reporting. These methods have been developed to reduce redundant transmissions and extend the lifetime of WSNs [16]. The energy efficiency in WSNs is improved by selecting cluster heads using an enhanced kernel Fuzzy-C-Means method and optimizing routing with a new CP-BMO algorithm, which significantly reduces energy consumption and improves packet delivery and network lifetime compared to other approaches [17]. Table 1 summarizes the research works.

Table 1. Summary of Research works

Ref	Technique / Model	Method	Application domain	Findings	Limitations
[1]	m-BIRCH	Incremental hierarchical clustering using CF-tree with minimal memory	High-dimensional visual data (SIFT, Hopkins 155)	Supports online clustering, density-aware, memory efficient	Designed for visual data, not for WSNs
[2]	PSO + MCST	Two SenCars + SDMA for mobile data collection using PSO-based CH selection and MCST routing	Mobile WSN	Improves performance, reduces latency and energy consumption	Requires mobile sinks and special antennas
[3]	BIRCH + Local Structure Mapping	Semi-supervised Bayesian drift detection using BIRCH ensembles	Streaming data / concept drift	Detects recurring vs novel concepts, improves classification	Not designed for energy-constrained networks
[4]	AACDIC	Energy-efficient spectrum sensing via adaptive clustering	Cognitive radio networks	Reduces power by 9.64%, energy usage by 24.23%	Focused on CRNs, not general WSN data aggregation
[6]	PSO + MST topology	MST defines neighborhood for multimodal optimization,	Multimodal global optimization	Improves diversity, prevents genetic drift, outperforms benchmarks	Not applied to routing or WSN clustering in original study

		removes heavy edges			
[9]	Dynamic MST maintenance	Efficient MST updates for dynamic weighted graphs	Graph optimization / dynamic networks	Retains MST with minimal recomputation	Does not address WSN-specific energy constraints
[13]	Hybrid PSO + Improved LEACH	PSO for optimal CH selection + dynamic CH rotation in LEACH	WSN clustering	55% node survival, 28% reduced energy consumption	Still relies on LEACH assumptions and static topology
[17]	PSO vs ACO	PSO for optimal placement; ACO for routing (wildfire WSN)	Environmental monitoring (wildfire detection)	PSO converges faster, ACO used only for routing	Lacks unified hybrid design
[14]	PSO + Fuzzy clustering	Fuzzy grouping + PSO-based CH selection	IoT / WSN	Energy ↓ 52%, throughput ↑112%, PDR ↑83%, lifetime ↑48%	Requires fuzzy membership computation overhead
[16]	Adaptive clustering + controlled reporting	Minimizes redundant transmission using intelligent routing	Generic WSN	Extends network lifetime through adaptive sampling	No advanced metaheuristics applied
[17]	Kernel FCM + CP-BMO	Enhanced fuzzy clustering + optimization-based routing	WSN	Reduces energy and improves lifetime over others	Complex hybrid, not tested with mobile BS

Together, these advancements highlight the research gap where swarm based and graph-based methods improve the WSN performance, but there are only limited work combining hierarchical clustering with swarm and MST topology. This motivates the development of hybrid models which includes hierarchical clustering, bio-inspired optimization, and graph-aware routing to enhance the scalability, energy efficiency and adaptability in WSNs.

2.1. GAP Identified

Considering the extensive use of clustering and routing techniques in WSNs, conventional algorithms continue to have substantial scalability, flexibility and energy efficiency constraints [4]. Most typical clustering approaches, such as LEACH and HEED, assume static network conditions and uniform nodes, which results in inefficient energy use and premature node failures in dynamic IoT deployments. These systems frequently neglect the spatial distribution of nodes and fail to dynamically respond to changes in node density or energy levels, resulting in imbalanced cluster formation and communication bottlenecks [8].

Real-time reactivity and contextual awareness are commonly lacking in conventional routing systems. In highly populated networks, typical approaches ignore

details concerning the local structure of nodes, resulting in faulty routing and ineffective node management. The designed routing system is inflexible, limiting its effectiveness in complex and diverse contexts.

Many researchers have pointed out the drawbacks of traditional clustering approaches. Static clustering algorithms struggle to account for real-time energy fluctuations. Intelligent routing protocols, such as ACO, outperform conventional techniques in terms of energy efficiency and network lifetime. The work addresses a hybrid and metaheuristic network by taking into account all of the advantages and disadvantages of routing strategy creation. It uses a BIRCH-based clustering and routing model linked with POS-MST for energy-efficient and scalable WSN networks.

3. Problem Statement

In IoT applications, but its usefulness is restricted by the energy efficiency of battery-powered devices. Conventional models do not account for factors such as node diversity, energy swings, or climate volatility. Furthermore, in real-world scenarios, these networks are influenced by concept drift and local data trends. Various approaches such as PSO, ACO, and BIRCH clustering have demonstrated advances, however overall energy efficiency has not been

achieved. As a result, a hybrid network has been developed to improve energy efficiency and scalability.

4. Novelty and Contributions

Unlike prior hybrid clustering approaches that combine metaheuristic for static routing, the study integrates hierarchical clustering (BIRCH) and swarm-based routing (ACO) in a software-defined WSN for adaptive load balancing. The PSO-MST integration introduces graph-aware topology control within swarm optimization, rarely explored in WSNs. Emphasize dynamic base-station mobility and real-time adaptability, which was lacking in the earlier works.

5. Methodology

A hybrid data aggregation system for enhancing the WSN network is illustrated in figure 1. The figure illustrated the challenges faced and the motivation of the study. The model presents two hybrid frameworks. In the first framework, BIRCH and ACO is employed for selecting the cluster head and position the mini base station (MBS). In the second framework, PSO is utilized for dynamic selection of cluster head and base station. PSO is integrated with MST for identifying the energy efficient movement patterns for the base station. The network efficiency is evaluated based on the factors of throughput, data latency, and network lifetime and energy efficiency.

5.1 Framework 1: Birch Combined With ACO

In the initial stage, BIRCH is integrated with ACO for finding the cluster heads and for positioning the mini base station. BIRCH is a well-suited algorithm for a large dataset, which requires minimal memory for the allocation. It is a hierarchical clustering method that

adaptively clusters the incoming data. These data are represented as a modified tree structure referred to as the clustering feature tree [18]. As indicated in Eqn. 1, each node in the CF Tree comprises a cluster summary depicted as a Clustering Feature (CF) triple:

$$CF = \{N, LS, SS\} \tag{1}$$

Where, N is the number of data points in the cluster. $LS = \sum_{i=1}^N \vec{x}_i$ is the linear sum of all data vectors. $SS = \sum_{i=1}^N \vec{x}_i^2$ is the sum of squared data vectors. The CF triple allows BIRCH to represent a cluster without storing individual data points, enabling scaling and incremental clustering. The linear sum (LS) and squared sum (SS) support efficient computation of key statistics like the centroid, radius and variance during the cluster merging and splitting without revisiting the raw data.

The centroid of a cluster is given by the Eqn. 2, represents the geometric centre of the cluster and is later used to select cluster heads or estimate transmission distance to the BS. Since energy consumption in WSN is highly related to the transmission distance, centroid-based decision helps to minimise energy usage and balances load.

$$\vec{c} = \frac{LS}{N} \tag{2}$$

The distance between two CF entries (used to merge clusters or assess similarity) is computed as in Eqn. 3. It measures the distance between two clusters using their compressed CF statistics. This enable BIRCH to determine whether the two cluster needs to be merged based on their spatial similarity without accessing individual sensor readings. This distance-based approach reorganizes cluster when new nodes are created and joined or when network topology changes.

$$D(CF_1, CF_2) = \left\| \frac{LS_1}{N_1} - \frac{LS_2}{N_2} \right\| \tag{3}$$

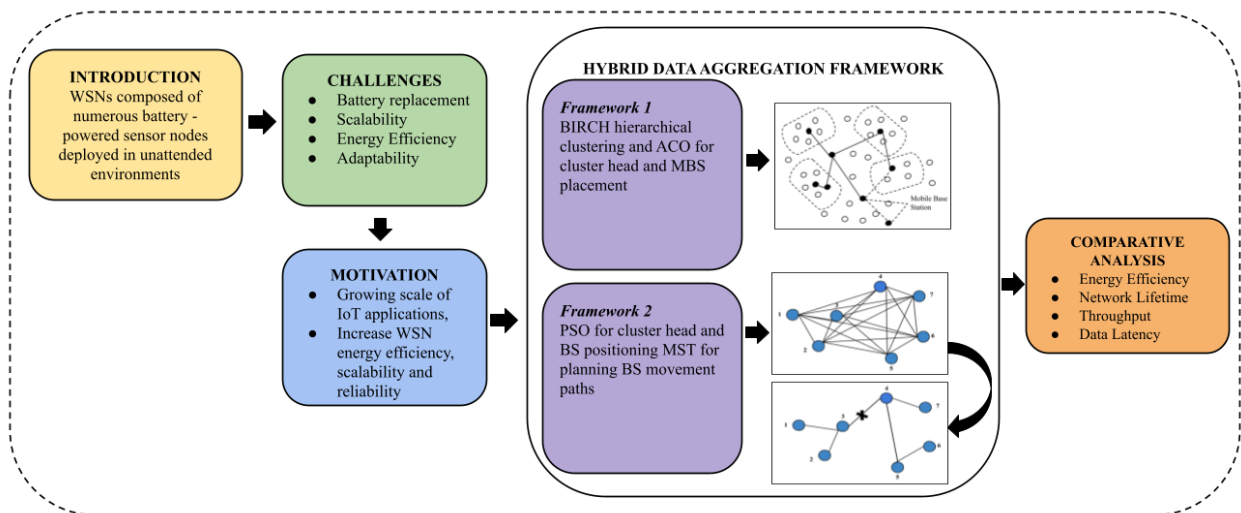


Figure 1. Schematic Framework of the Proposed Study

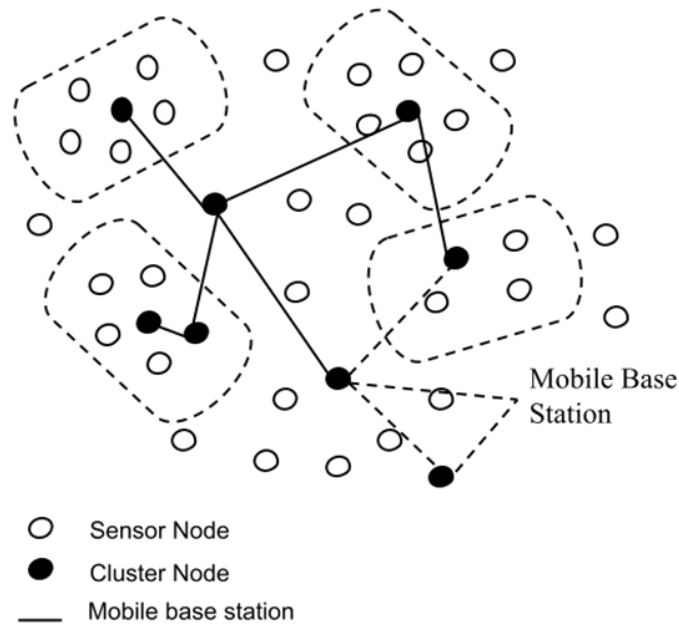


Figure 2. BIRCH and ACO-based clustering and routing strategy.

BIRCH reduces memory and transmission costs by compressing large data sets into compact CF Trees, which enable iterative grouping without retaining all data points. BIRCH in WSNs reduces intra-cluster communication by forming energy-efficient, spatially compact clusters.

ACO is a probabilistic metaheuristic based on ant foraging behaviour that was first created by [19]. Because of its decentralized and flexible nature, ACO is widely used in wireless sensor networks for cluster head selection, routing, and mobile base station path planning. The core premise is that artificial ants travel along trails and deposit pheromones, with the most efficient paths receiving more pheromones and thereby influencing future ant decisions. The probability of an ant migrating from node i to node j is computed as in Eqn. 4. Higher pheromone values represent past successful routes, while η_{ij} biases selection towards shorter distances.

$$P_{ij}(t) = \frac{[\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}(t)]^\beta}{\sum_{k \in N_i} [\tau_{ik}(t)]^\alpha \cdot [\eta_{ik}(t)]^\beta} \quad (4)$$

Where $\tau_{ij}(t)$ is the pheromone value on edge (i, j) , $\eta_{ij}(t) = 1/d_{ij}$: heuristic value, typically inverse of distance, α, β are the parameters controlling the influence of pheromone vs heuristic, and N_i is the set of neighbouring nodes of node i . Pheromone levels are updated using Eqn. 5. The evaporation term $(1 - \rho)$ prevents pheromone saturation, allowing ants to forget the outdated paths and explore alternative path, which is more crucial in the energy-depleting and mobile WSNs. The reinforcement term $\Delta\tau_{ij}$ increases pheromone on efficient, energy-saving routes, enabling the network gradually converge to low-cost communication paths while retaining its adaptability to topology changes.

$$\tau_{ij}(t + 1) = (1 - \rho) \cdot \tau_{ij}(t) + \Delta\tau_{ij}(t) \quad (5)$$

Where the evaporation rate is $\rho \in [0, 1]$, and the pheromone deposited based on route quality is $\Delta\tau_{ij}(t)$. ACO is suitable for WSNs because it enables adaptive routing and effective base station scheduling, resulting in lower energy usage and congestion.

The merging of BIRCH and ACO enables a powerful hierarchical and adaptive clustering framework for WSNs. BIRCH first organizes the sensor nodes according to their spatial proximity and creates a CF tree structure. Within each cluster, ACO chooses cluster heads based on node energy levels, proximity, and connectivity, balancing load and maximizing coverage. ACO identifies mobile base station places by choosing the shortest journey distance and energy cost. This hybrid approach allows for compact clusters with minimal intra-cluster communication (via BIRCH). Dynamic and energy-efficient head selection and routing (using ACO).

The mentioned approach outperforms static clustering because it helps the WSN adapt to a changing topology, loss of nodes, and changing load circumstances in real time, which extends network lifetime and decreases energy imbalance between nodes. Figure 2 depicts the hybrid routing strategy using BIRCH and ACO in WSN. BIRCH is first used to group nodes into tight groups based on proximity and energy. Using pheromone updates, the routing based on ACO protocol, selects optimal communication channels both within and among clusters for effective data transmission.

5.2 Framework 2: PSO with MST

Using the concept of bird flocks [8], PSO is developed. PSO is a population-based optimization

approach. The environment is represented by flocks of birds soaring through air, guided by the bird nearest to the food supply. PSO, for example refers to the birds as a flock of particles, where each particle represents a possible solution to the problem. It solves optimization problems by exploiting the social aspect of flock behavior, as birds do. Flocks of particles explore space in specific dimensions to discover the optimal solution.

PSO achieves a unique blend of exploration and exploitation. Exploration helps to broaden the solution space, whereas refinement focusses on promising solutions. A suitable balance of the two strategies is crucial for improving the optimizer performance.

Using PSO in wireless sensor networks (WSNs) reduces the amount of data and energy required to communicate within a cluster by finding the optimal location for cluster heads and mobile base stations.

Each particle (representing a potential cluster head/base station position) updates its velocity (Eqn. 6) and position (Eqn. 7) using:

$$a_i(t+1) = w \cdot a_i(t) + b_1 \cdot y_1 \cdot (p_i - x_i(t)) + b_2 \cdot y_2 \cdot (s - x_i(t)) \quad (6)$$

$$x_i(t+1) = x_i(t) + a_i(t+1) \quad (7)$$

Where $a_i(t)$ is the velocity of the particle i . $x_i(t)$ is the current position of particle i . p_i is the personal best position of particle i . s is the global best position found by the swarm. w is the inertia weight. b_1 and b_2 are the cognitive and social coefficients. y_1 and y_2 are the random numbers in $[0,1]$. PSO allows the system to converge rapidly to optimal configurations of cluster heads or base station positions, ensuring reduced data transmission energy and fewer retransmissions due to congestion or path loss.

Eqn. 6 defines how each particle updates its velocity based on three main components,

- Inertia term $w \cdot a_i(t)$ preserves momentum from the previous iterations, preventing abrupt changes. Large inertia encourages global exploration, while smaller ones enable fine tuning.
- Cognitive term $b_1 \cdot y_1 \cdot (p_i - x_i(t))$ drives the particle back towards its own best-known solution, enabling personal learning and local exploitation
- Social term $b_2 \cdot y_2 \cdot (s - x_i(t))$ attracts the particle toward the best solution found by the entire swarm, enhancing collective convergence.

Together, these three components allow PSO to balance exploration and exploitation, which is essential when dynamically selecting cluster heads or locating

mobile BS in changing WSNs. The updated velocity is added to the previous position in Eqn. 7, producing a new solution candidate. As updates require basic arithmetic operations, PSO is computationally lightweight and suitable for resource-limited nodes.

The MST network connects all nodes in a network while minimizing the cost of all edges, such as energy consumption and distance. Kruskal's algorithm, a greedy graph-based algorithm widely used to build low-cost network topologies, is a common implementation. MST is specified as picking a subset of edges in a connected, weighted undirected graph that spans all vertices without cycles and has the lower edge weight. MST, was developed by Brouvka in the year 1926, is crucial in fields of transportation planning, financial marketing, communication network design, and analysis of brain network. It is also useful in power grid planning and power distribution, requires optimal connectivity. Although efficient approaches such as Kruskal's and Prim's exist, the growing complexity and dynamic nature of real-world networks provide challenges for real-time MST maintenance, leading to the development of more complicated dynamic algorithms [11].

Graphs are generated based on distribution of the particles. Each particle is considered to be a vertex in a chart. Each pair of particles has a weighted edge connecting them. The Euclidean distance determines the weight of the edge between particles i th and j th as represented in Eqn. 8.

$$w_{ij} = \left\| p_{best_i} - p_{best_j} \right\| \quad (8)$$

w_{ij} is the edge weight and is defined as the Euclidean distance between the personal best (pbest) positions of the particles i and j . The use of memory best values rather than current positions makes the MST representation more stable and less sensitive to momentary oscillations during optimization. The topology consistency is improved during routing.

The distance between particles is estimated using their personal best (memory-best) positions rather than their current positions, as the memory-best is a more stable and reliable reference. These distances are then combined to create a complete graph, which is then overlaid with a Minimum Spanning Tree. In the MST, edges with the highest weights are more likely to connect particles from various niches. To decrease genetic drift, the highest weighted edges are deliberately removed, breaking the MST into numerous connected components. Each component arranges particles that are geographically close in the search space. The presence of an edge between any two particles in the MST structure establishes their neighbourhood relationship.

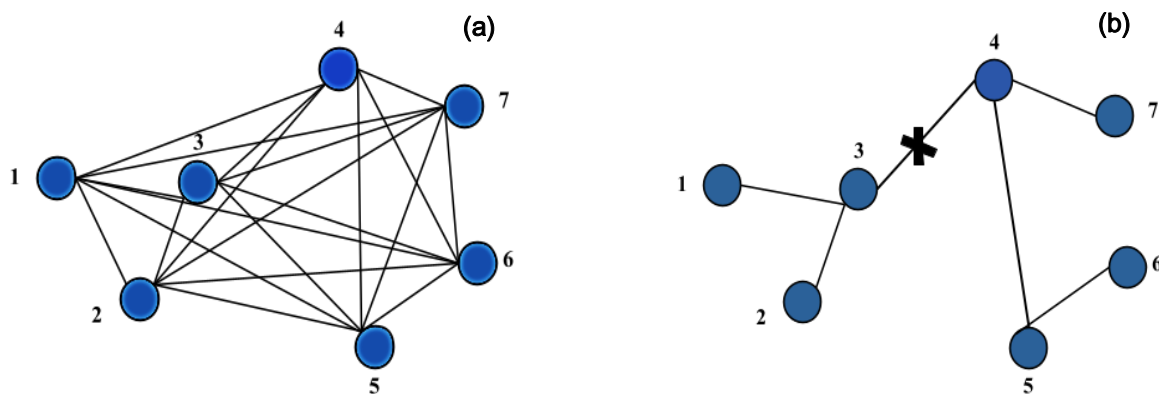


Figure 3. MST Topology (recreated from [10])

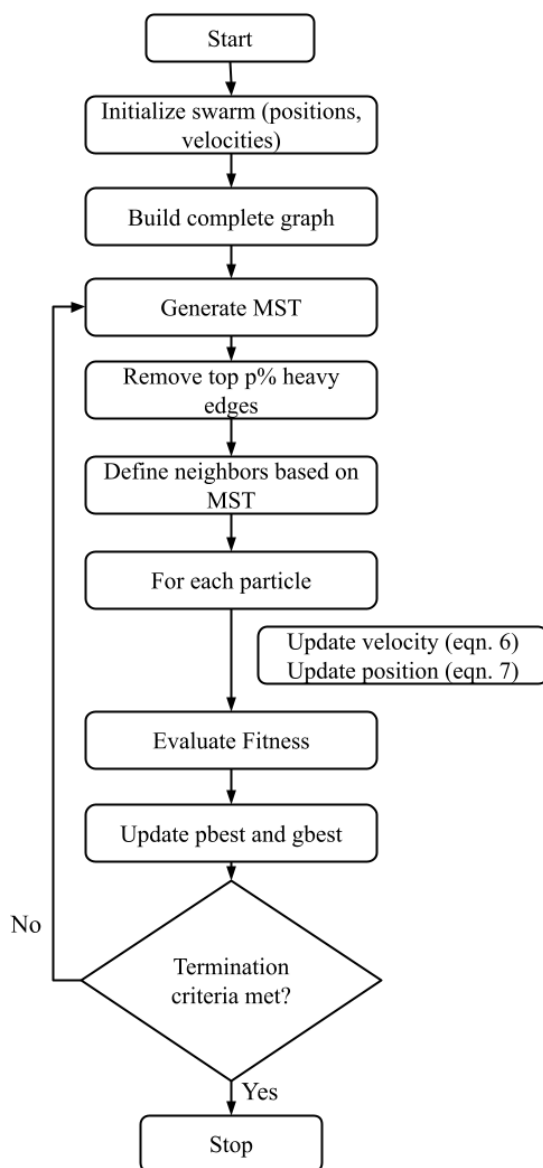


Figure 4. Flowchart of PSO-MST

The integration of MST topology with PSO has resulted in significant gains in multimodal problem solution, providing good justification for its use in routing. At each iteration, MST-based PSO generates a minimum spanning tree from the particle distribution,

resulting in the formation of particle neighborhood. This adaptive topology captures spatial interactions between particles using a minimum number of edges, increasing convergence speed and solution variety [8]. The results provide strong evidence for utilizing a PSO-MST hybrid

model in routing scenarios where maintaining optimal and diverse paths is crucial to network performance. Figure 3 shows the example of building the MST topology. The figure 3a) depicts the weighted edge that connects to each pair of vertices. Edge weight is calculated by taking the Euclidean distance between comparable particles in the search space. Fig. 3b) is the MST generated from the weighted graph. The longest edge between three and four particles is clipped to form and maintain distinct niches. Each particles have a neighborhood list. The neighbors are identified by inspecting the remaining edges in the MST.

Unlike conventional PSO topologies, the MST-based structure is a dynamic, distance-driven structure with a global perspective. It accurately displays particle dispersion with few critical edges. The major benefits of MST are dealing with multimodal issues are its capability to incorporate local and global information and evolve with particle movement, decreasing information latency. In addition, MST-defined neighbors are geometrically close, facilitating local search and fine-tuning. Removing high-weight edges helps to keep numerous stable niches.

Figure 4 illustrates the flowchart of PSO-MST model. The approach starts with swarm initialization, which distributes particles randomly across the search space. The particles are then joined to form an entire graph, with the underlying topology determined by MST. To promote variation and niche preservation, a specific percentage of the MST's highest-weighted edges are removed. This phase helps to divide the graph into niches. The revised MST is then used to define each particle's neighbors allowing particles to communicate with geometrically close peers and thereby enhancing local search capacity.

The velocities and placements of the particles are altered based on the feedback and best outcomes from their neighbors. Following movement, each particle's fitness is evaluated, and their global and personal bests ("gbest" and "pbest") are adjusted accordingly. This loop is run until a stop statement is met, like the number of iterations or an acceptable fitness value, at which point the algorithm exits. This system constantly adjusts the neighborhood structure to strike an optimum balance between exploration and exploitation. The implemented pseudocode is shown below.

Pseudocode for Framework 1

Algorithm 1. BIRCH + Ant Colony Optimization (ACO) Based Data Aggregation

Input:

N: number of sensor nodes

numCHs: desired number of cluster heads

pos(N): sensor node positions in 2D

α, β : ACO parameters

ρ : pheromone evaporation rate

numIter: number of iterations in ACO algorithm.

Output:

CH_set: final cluster heads

Routes: optimized routing paths

Metrics: {throughput, delay, energy efficiency, standard deviation, mean}

Step 1: Initial clustering using BIRCH

Clusters \leftarrow BIRCH

Step 2: Initialize ACO parameters

$\tau \leftarrow$ initialize pheromone matrix (N)

$\eta \leftarrow$ compute visibility (pos)

Step 3: ACO optimization for routing

For iter = 1 to numIter do

For each ant k do

Current \leftarrow random_start_node ()

visited \leftarrow {current}

While |visited| < N do

Transition probability using Eqn. 9

$$P_{ij} \propto (\tau_{ij})^{\alpha} * (\eta_{ij})^{\beta} \quad (9)$$

For each neighbor j not in visited do

$$P[j] \propto (\tau[\text{current}][j])^{\alpha} * (\eta[\text{current}][j])^{\beta} \quad (10)$$

End for

next \leftarrow roulette wheel selection (p)

visited \leftarrow visited \cup {next}

update pheromone using Eqn. 10.

$$\Delta\tau$$

\leftarrow compute pheromone deposit (current, next)

$$\tau[\text{current}][\text{next}]$$

$$\leftarrow (1 - \rho) * \tau[\text{current}][\text{next}] + \Delta\tau$$

$$\text{current} \leftarrow \text{next}$$

End while

End for

End for

Step 4: Select cluster head

$$CH_{set}$$

\leftarrow select_top_pheromone_nodes(τ , numCHs)

Step 5: Compute base station

$$BS \leftarrow \text{centroid}(CH_{set})$$
Step 6: Compute performance metrics

For each node i do

$$d \leftarrow \text{DISTANCE}(i, \text{assigned CH})$$

$$\text{Delay}[i] \leftarrow \frac{d}{\frac{\text{txspeed}}{\text{packetsize}}}$$

$$\text{energy}[i] \leftarrow E_{tx} + E_{amp} * d^2$$

End for

$$\text{Throughput} \leftarrow \frac{\text{total}_{bits}}{\sum \text{delay}[i]}$$

$$\text{efficiency} \leftarrow \frac{\text{total}_{bits}}{\sum \text{energy}[i]}$$

Return {CH_set, routes, metrics}

Pseudocode for Framework 2

Algorithm 1. PSO + MST based data aggregation

Input:

N: number of sensor nodes

numCHs: desired number of cluster heads

pos(N): node coordinates

maxIter: number of iterations in PSO.

$\omega, C1, c2$: PSO parameters

Output:

CH_set: final cluster heads

Routes: optimized routing paths

Metrics: {throughput, delay, energy efficiency, standard deviation, mean}

Step 1: Initialize PSO particles

For each particle p do

$$p.\text{positions} \leftarrow \text{random}_{CH_{positions}(\text{numCHs})}$$

$$p.\text{velocity} \leftarrow \text{random}_{\text{vector}}()$$

$$p.\text{pbest} \leftarrow p.\text{position}$$

End for

$$g\text{best} \leftarrow \text{best}_{\text{particle}}$$
Step 2: PSO optimization loop

For iter = 1 to maxIter do

For each particle p do

$$CH_{coords} \leftarrow \text{Reshape}(p.\text{position})$$

// Fitness = sum of distances (minimize)

$$p.\text{fitness} \leftarrow \sum \text{Dist}(\text{node}_i, \text{nearest CH})$$

If $p.\text{fitness} < \text{fitness}(p.\text{pbest})$ then

$$p.\text{pbest} \leftarrow p.\text{position}$$

End If

If $p.\text{fitness} < \text{fitness}(g\text{best})$ then

$$g\text{best} \leftarrow p.\text{position}$$

End If

// Update velocity using Eqn. 6

$$p.\text{velocity} \leftarrow w * p.\text{velocity} + c1 * \text{rand} * (p.\text{pbest} - p.\text{position}) + c2 * \text{rand} * (g\text{best} - p.\text{position})$$

// Update position using Eqn. 7

$$p.\text{position} \leftarrow p.\text{position} + p.\text{velocity}$$

End for

End for

Step 3: Final CH selection

$$CH_{set} = \text{RESHAPE}(g\text{best})$$
Step 4: Build MST over CHs

$$D \leftarrow \text{Distance}_{\text{matrix}}(CH_{set})$$

$$MST \leftarrow \text{Minimum spanning tree}(D)$$
Step 5: Compute Metrics

For each i do

$$d \leftarrow \text{distance}(i, \text{next hop in MST})$$

$$\text{delay}[i] \leftarrow d / \left(\frac{\text{txspeed}}{\text{packetsize}} \right)$$

$$\text{energy}[i] \leftarrow E_{tx} + E_{amp} * d^2$$

End for

$$\text{Throughput} \leftarrow \frac{\text{total}_{bits}}{\sum \text{delay}[i]}$$

$$\text{efficiency} \leftarrow \frac{\text{total}_{bits}}{\sum \text{energy}[i]}$$

Return {CH_set, MST, metrics}

6. Simulation Setup

The section briefs on the network parameters, simulation environment and the evaluation metrics of the hybrid model. MATLAB environment is employed for the simulation and optimization. Table 3 displays the network parameters of the simulated model.

7. Performance Metrics

7.1 Energy Consumption

Energy consumption is defined as the maximum energy utilized by all sensor nodes while sensing, transmitting, receiving, and processing activities across the simulated rounds [20].

The energy consumed by a node to transmit a k -bit message over the distance d is calculated as in Eqn. 11.

$$E_{tx}(k, d) = E_{elec} \cdot k + E_{amp} \cdot k \cdot d^2 \quad (11)$$

Similarly, the energy to receive the k -bit message is calculated using Eqn. 12.

$$E_{rx}(k) = E_{elec} \cdot k \quad (12)$$

Where $E_{elec} = 50 \frac{nJ}{bit}$, $E_{amp} = 100 \frac{pJ}{bit/m^2}$, $k = 4096 \text{ bits}$, d is the distance between the sender and the receiver.

Where $E_{elec} = 50 \frac{nJ}{bit}$, $E_{amp} = 100 \frac{pJ}{bit/m^2}$, $k = 4096 \text{ bits}$, d is the distance between the sender and the receiver.

7.2 Throughput

Throughput is the total number of packets successfully delivered to the base station throughout the simulated period. It is calculated as in Eqn. 13.

$$\text{Throughput} = \frac{\text{Total number of packets received by BS}}{\text{Total Simulation time}} \quad (13)$$

7.3 Data Latency

Data latency refers to the average time it takes for a packet to transit from a sensor node to the base station. The delay is computed using Eqn. 14.

$$\text{Average Latency} = \frac{1}{N} \sum_{i=1}^N (T_{receive_i} - T_{send_i}) \quad (14)$$

When N is the total number of packets received by BS, T_{send_i} is the packet's time of transmission, and $T_{receive_i}$ is the packet's time of reception by BS.

8. Results and Discussion

A comprehensive investigation of the results is presented. The models are evaluated based on the energy usage, data delay, throughput and network lifetime. The results demonstrate that BS relocation and optimised based grouping can contribute to increased network efficiency. To evaluate the effectiveness of the proposed work, the performance with those of LEACH [21], PSO [13], and ACO [22] are compared.

As shown in figures 5-(i), (iii), (v) and (vii), clustering outcomes are presented for networks consisting of 50, 75, 100, and 125 sensor nodes, respectively. A blue circle represents the deployed

sensor nodes, a red square represents selected cluster heads, and a black star symbolizes the BS position. BIRCH clusters sensor nodes into hierarchical groups using physical closeness to arrange them in an orderly manner. The ACO algorithm selects ideal cluster heads within the clusters and determines the best location for the mobile base station after initial clustering. Based on the graphs, cluster heads are scattered over a wide area, especially when node density is high, ensuring broad coverage with little communication distance between clusters.

Increasing the number of nodes from 100 to 125, causes BIRCH and ACO to generate a greater number of clusters. When the node size increases the intra-cluster communication costs and competition transmission slot increases. In spite of these conditions, the network displays the ability to cluster to a larger node population. The subfigures (ii), (iv), (vi), and (viii) show the clustering and routing results of the PSO and MST frameworks for the same rising node density. In these maps, sensor nodes are represented by blue markers, cluster heads by green squares, and mobile BS locations by yellow markers. The grey lines connecting the BS positions are MST-based pathways used to optimize BS movement and communication routing.

In this framework, PSO is used to choose cluster heads by modelling the swarm intelligence of particles moving in a multidimensional space to discover the best solutions. Depending on the topology of the network, the distribution of nodes, and the availability of energy, cluster heads are strategically positioned.

Then, MST is used to determine the best energy-efficient path for the cluster head or to interact with numerous cluster heads simultaneously.

Spatial and compact clustering is observed across all node densities. MST ensures that base stations transmit data along the shortest path possible, which reduces communication delay and energy consumption. Through the proposed framework, clusters and base stations remain consistent as the node size increases. As a result, the network load increases and energy efficiency improves. ACO clustering methods and BIRCH are suitable for static and dynamic environments. The framework effectively allocates the nodes, reducing clustering node overlap in moderately dense networks. Node count increases as a result of this technique, which reduces communication overhead.

A strategic cluster head selection is based on the overall optimization goals based on the PSO and MST frameworks. With MST-based path planning, the communication framework remains efficient and adaptable. Energy consumption and data latency are reduced as a result of the integration, and the network's lifespan is also prolonged. When the overall results are analysed, PSO and MST based framework performed well in terms of scalability, adaptability and clustering

efficiency. Large-scale WSNs can be optimized effectively with PSO and MST, despite limited resources, by combining the two models. The further analysis includes the evaluation of the model based on throughput, data latency and energy efficiency. Existing algorithm LEACH is considered for the comparison for the proposed framework. The models are individually evaluated and the results are presented in the table.

Table 4 presents the throughput analysis of the models in the study. The results indicate that PSO and MST combined model achieved better performance compared to the other models. When the number of nodes increases from 50 to 125, there is substantial

evidence in the increase in throughput from 247.94 ± 138.19 kbps to 635.61 ± 179.13 kbps. The existing model LEACH, though showed improvement in the values but didn't rank highest. This implies that LEACH limits in scalability and energy-efficiency. Furthermore, when the individual models are considered, PSO performed well in the smaller network sizes, and its overtaken slightly at 125 nodes by ACO model, implying that routing optimization becomes critical when the node size increases. BIRCH and ACO model comparatively showed better performance than LEACH, highlighting the impact of bio-inspired routing and clustering methods.

Table 3 Network Parameters

Parameter	Value / Description
Number of Sensor Nodes	50, 75, 100, 125 (to analyze scalability)
Deployment area	100m x 100m
Initial Node Energy	2 J/node
Transmission Range	25 -30 m
Packet Size	512 bytes
Base station type	Static (Framework 1), Mobile (Framework 2)
Energy model parameters	$E_{tx} = 50 \text{ nJ/bit}, E_{amp} = 100 \text{ pJ/bit/m}^2$
Mobility Model	Controlled trajectory (for mobile BS)
Cluster Head Percentage	5–10% of total nodes
Simulation Rounds	1000–2000 rounds
Node Distribution	Uniform random deployment

Table 4. Throughput Vs Number of Nodes

Number of Nodes	Throughput (kbps)				
	LEACH	PSO only	ACO only	PSO and MST	BIRCH and ACO
50	152.99 ± 338.06	247.94 ± 138.19	231.87 ± 141.69	247.94 ± 138.19	257.80 ± 168.91
75	245.15 ± 401.68	375.26 ± 160.62	374.10 ± 250.32	375.26 ± 160.62	388.48 ± 172.26
100	425.28 ± 628.89	517.80 ± 207.23	476.99 ± 360.12	517.80 ± 207.23	518.19 ± 195.41
125	484.32 ± 810.91	635.61 ± 179.13	615.22 ± 479.71	635.61 ± 179.13	640.05 ± 328.01

Table 5. Delay Vs Number of Nodes

Number of Nodes	Delay (ms)				
	LEACH	PSO only	ACO only	PSO and MST	BIRCH and ACO
50	1.396 ± 0.331	0.828 ± 0.044	0.886 ± 0.054	0.728 ± 0.044	0.897 ± 0.050
75	1.280 ± 0.211	0.820 ± 0.036	0.824 ± 0.051	0.720 ± 0.036	0.892 ± 0.036
100	0.981 ± 0.151	0.792 ± 0.032	0.862 ± 0.062	0.702 ± 0.032	0.891 ± 0.031
125	1.087 ± 0.225	0.806 ± 0.022	0.836 ± 0.067	0.700 ± 0.022	0.802 ± 0.043

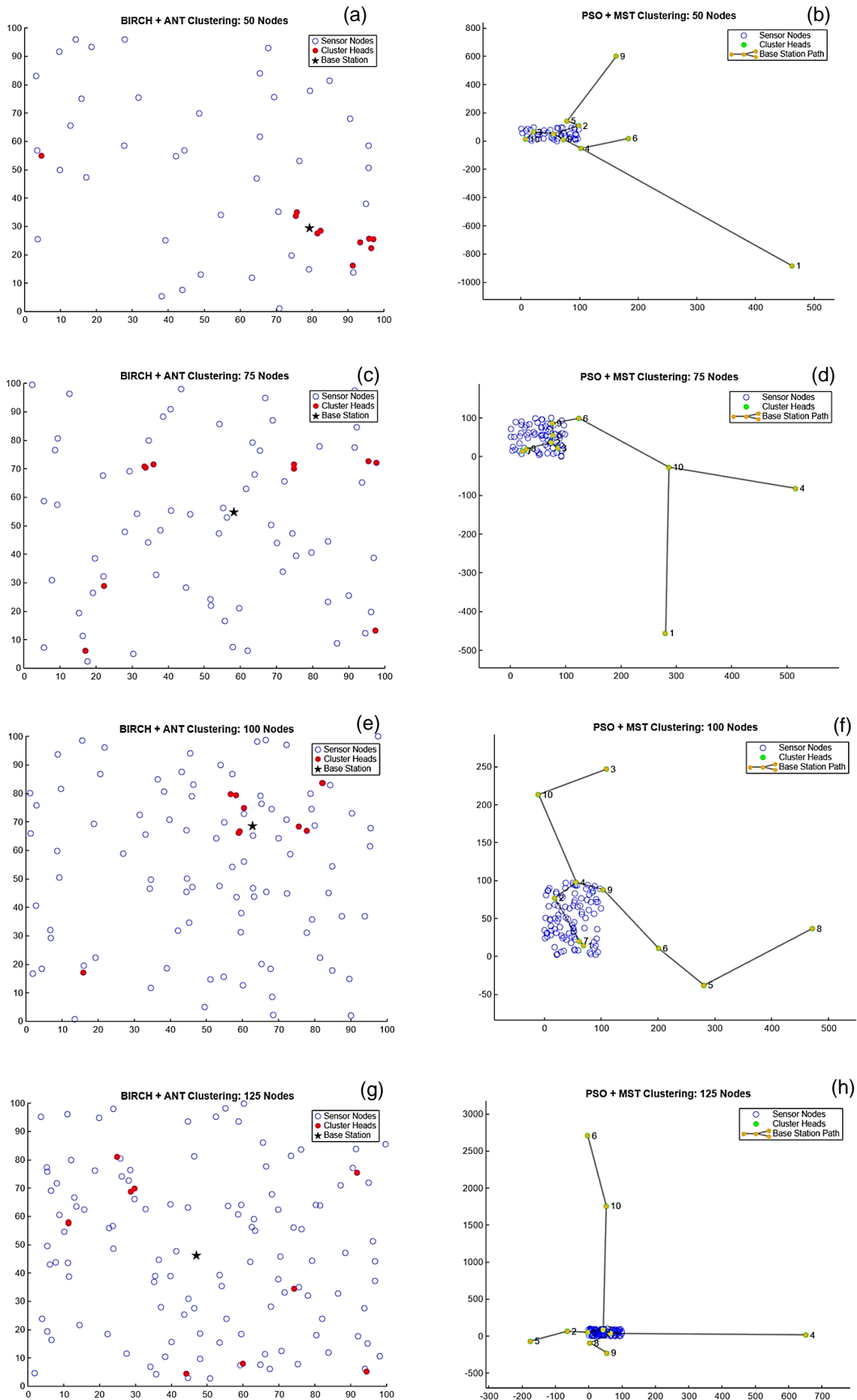


Figure 5. Clustering Plots

Table 6. Energy Efficiency Vs Number of Nodes

Number of Nodes	Energy Efficiency (Mbits/J)				
	LEACH	PSO only	ACO only	PSO and MST	BIRCH and ACO
50	1.390 ± 221.62	1.580 ± 239.35	1.518 ± 412.10	3.335 ± 134.25	1.580 ± 239.35
75	1.305 ± 735.71	1.555 ± 276.30	1.520 ± 493.41	3.772 ± 256.42	1.555 ± 276.30
100	1.288 ± 391.95	1.563 ± 420.47	1.495 ± 421.61	3.834 ± 868.34	1.563 ± 420.47
125	1.308 ± 121.27	1.525 ± 175.23	1.474 ± 944.46	3.943 ± 225.20	1.525 ± 175.23

Table 5 represents the delay values. The analysis reveals that the lowest end-to-end delay is achieved by PSO-MST framework. Even when the number of nodes increases, the delay under PSO-MST remains stable and minimal ranging from 0.728 ± 0.044 ms to 0.700 ± 0.022 ms. This value indicates the robustness in dense network conditions and the ability to migrate congestion and routing overhead. Across all the scenarios, LEACH model exhibits the highest delay. Indicating that the model fails to perform in increased traffic and network scalability. When the individual methods are considered, PSO performed well in terms of delay compared to ACO model, implying optimal deployment has a stronger influence on delay reduction than routing optimization alone. BIRCH and ACO offered improved performance over conventional LEACH, reflects the benefit of hierarchical clustering and bio-inspired optimization.

An effective energy routing technique is crucial for WSN data transmission [23]. Table 6 shows the energy efficiency results of the models. The results indicate that PSO-MST and PSO only models achieve the highest and most consistent performance across all node densities, values ranging between 3.335 ± 134.25 and 3.943 ± 225.20 Mbits/J. this proves that PSO when combined or individually executed enables balanced energy consumption while ensuring efficient data handling. BIRCH and ACO perform steadily, close to PSO-only, highlighting the effectiveness of hierarchical clustering combined with bio-inspired routing. In contrast, ACO only exhibits lowest efficiency across all network sizes, due to additional routing overhead when sensor placement is not optimized. Moderate energy efficiency is showed by LEACH. Combining hybrid models like PSO, ACO in clustering and routing, increases the efficiency and throughput [24].

Overall, the result analysis infers that PSO-MST model offer better trade-off between energy efficiency, delay and throughput. By integrating optimal sensor deployment through PSO and effective routing through MST, the combined model achieves significant performance. PSO alone performs well in both smaller networks and energy-related metrics, it is the addition of MST that enables better routing stability even under network traffic. BIRCH and ACO outperform

conventional LEACH due to their hierarchical clustering and bio-inspired optimization.

The findings demonstrate that neural network-based prediction outperforms classical aggregation in terms of energy efficiency, transmission reduction, and network longevity [25]. While PSO and ACO improve performance alone, their combination with prediction produces the most consistent and accurate results. Under identical network setups, the hybrid technique consistently outperforms traditional methods.

Notably, all scenarios are evaluated under the same network and energy conditions, ensuring a fair and consistent comparison. The results clearly demonstrate that the proposed modified PSO and MST algorithm outperforms the conventional methods described in [23, 22] and several other competing protocols across all assessed parameters.

8. Conclusion

The comparative analysis of PSO, ACO, BIRCH and ACO, PSO and MST, and LEACH across varying node densities demonstrates that while LEACH consistently achieves the highest mean performance, shows instability due to large standard deviation, making it less reliable for real-time deployment. PSO-based methods, PSO and MST exhibit more stable and predictable behaviour, with moderate mean and low variability values, making it suitable for WSN operations. Though BIRCH and ACO achieved better performance, the high variance at larger nodes reports to the sensitivity to network topology, while ACO alone displays inconsistent behaviour among various scenarios.

8.1 Limitations and Future Work

The study is limited by its reliance on only mean and standard deviation metrics, and a lack of analysis on computational overhead and real-time constraints. These limitations suggest that future work can incorporate additional performance metrics, and multi-objective optimization to evaluate the applicability of hybrid clustering and routing strategies in practical WSN models.

References

- [1] S.K. Madan, K.J. Dana, Modified balanced iterative reducing and clustering using hierarchies (m-BIRCH) for visual clustering. *Pattern Analysis and Applications*, 19, (2016) 1023-1040. <https://doi.org/10.1007/s10044-015-0472-4>
- [2] K. Vijayalakshmi, J.M. Manickam, Mobile data gathering using PSO and minimum covering spanning tree clustered WSN. *International Journal of Mobile Network Design and Innovation*, 8, (2018) 101. <https://doi.org/10.1504/IJMNDI.2018.092346>
- [3] Y. Wen, S. Liu, Semi-Supervised Classification of Data Streams by BIRCH Ensemble and Local Structure Mapping. *Journal of Computer Science and Technology*, 35, (2020) 295 - 304. <https://doi.org/10.1007/s11390-020-9999-y>
- [4] K.A. Sharada, T.R. Mahesh, S. Chandrasekaran, R. Shashikumar, V.V. Kumar, J.R. Annand, Improved energy efficiency using adaptive ant colony distributed intelligent based clustering in wireless sensor networks. *Scientific Reports*, 14, (2024). <https://doi.org/10.1038/s41598-024-55099-1>
- [5] S.M. Subinas, J.M. Mart'in, A.M. Ali, J. Sedano, Á.M. García-Vico, (2025) Knapsack and Shortest Path Problems Generalizations From A Quantum-Inspired Tensor Network Perspective. In *Proceedings of the 1st International Conference on Quantum Software – IQSOFT*, SciTePress. <https://doi.org/10.5220/0013489000004525>
- [6] J. Kennedy, R. Eberhart, Particle swarm optimization. *Proceedings of ICNN'95 - International Conference on Neural Networks*, IEEE, Australia. <https://doi.org/10.1109/ICNN.1995.488968>
- [7] T.M. Shami, A.A. El-Saleh, M. Alswaitti, Q. Al-Tashi, M.A. Summakieh, S. Mirjalili, Particle Swarm Optimization: A Comprehensive Survey. *IEEE Access*, 10, (2022) 10031 – 10061. <https://doi.org/10.1109/ACCESS.2022.3142859>
- [8] M. Shokouhifar, F. Fanian, M.K. Rafsanjani, M. Hosseinzadeh, S. Mirjalili, AI-driven cluster-based routing protocols in WSNs: A survey of fuzzy heuristics, metaheuristics, and machine learning models. *Computer Science Review*, 54, (2024) 100684. <https://doi.org/10.1016/j.cosrev.2024.100684>
- [9] Zhang, H., & Li, Z. (2020). Energy-Aware Data Gathering Mechanism for Mobile Sink in Wireless Sensor Networks Using Particle Swarm Optimization. *IEEE Access*, 8, 177219-177227. <https://doi.org/10.1109/ACCESS.2020.3026113>
- [10] M. Luo, H. Qin, X. Wu, C. Xiong, D. Xia, Y. Ke, Efficient Maintenance of Minimum Spanning Trees in Dynamic Weighted Undirected Graphs. *Mathematics*. 12(7), (2024) 1021. <https://doi.org/10.3390/math12071021>
- [11] M. Han, F. Meng, C. Li, Variance Feedback Drift Detection Method for Evolving Data Streams Mining. *Applied Sciences*, 14(16), (2024) 7157. <https://doi.org/10.3390/app14167157>
- [12] A.R. Sankaliya, PEGASIS: Power-efficient gathering in sensor information systems. *International Journal of Scientific Research in Science and Technology*, 1(5), (2015) 108-112.
- [13] S. Sharmin, I.B. Ahmedy, R. Md Noor, An Energy-Efficient Data Aggregation Clustering Algorithm for Wireless Sensor Networks Using Hybrid PSO. *Energies*, 15(5), (2023) 2487. <https://doi.org/10.3390/en16052487>
- [14] K. Rajaram, Optimal Deployment of Wireless Sensor Nodes using Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO). *International Journal for Research in Applied Science and Engineering Technology*. 12, (2024) 3764-3774. <https://doi.org/10.22214/ijraset.2024.62340>
- [15] C. Lei, An energy-aware cluster-based routing in the Internet of things using particle swarm optimization algorithm and fuzzy clustering. *Journal of Engineering and Applied Science*, 71(135), (2024). <https://doi.org/10.1186/s44147-024-00464-0>
- [16] N.K. Agrawal, N. Priya, P. Sinha, P. Singh, A. Jain, M. Kumar, (2024) Enhancing Data Aggregation Efficiency: Dynamic Energy-Aware Strategies in Wireless Sensor Networks. *2023 International Conference on Smart Devices (ICSD)*, IEEE, India. <https://doi.org/10.1109/ICSD60021.2024.10750980>
- [17] N.R. Maliseti, V.K. Pamula, Energy aware cluster-based routing in WSN using hybrid pelican-blue monkey optimization algorithm. *Evolutionary Intelligence*, 17, (2024) 2555 - 2575. <https://doi.org/10.1007/s12065-023-00903-6>
- [18] T. Zhang, R. Ramakrishnan, M. Livny, BIRCH: an efficient data clustering method for very large databases. *ACM SIGMOD Conference*, 25(2), (1996) 103 – 114. <https://doi.org/10.1145/235968.233324>
- [19] M. Dorigo, T. Stützle, (2003) *The Ant Colony Optimization*. The MIT Press. <https://doi.org/10.7551/mitpress/1290.001.0001>
- [20] P. Singh, R. Singh, (Energy-efficient QoS-aware intelligent hybrid clustered routing protocol for

- wireless sensor networks. Journal of Sensors, 2019(1), 2019) 8691878.
<https://doi.org/10.1155/2019/8691878>
- [21] G.K. Nigam, C. Dabas, ESO-LEACH: PSO based energy efficient clustering in LEACH. Journal of King Saud University - Computer and Information Sciences, 33(8), (2018) 947-954.
<https://doi.org/10.1016/j.jksuci.2018.08.002>
- [22] Y.S. Razooqi, M. Al-Asfoor, M.H. Abed, (2024) Optimize Energy Consumption of Wireless Sensor Networks by using modified Ant Colony Optimization. Acta Technica Jaurinensis, 17(3), 111–117.
<https://doi.org/10.14513/actatechjaur.00742>
- [23] J. Vellaichamy, S. Basheer, P.S.M. Bai, M. Khan, S. Kumar Mathivanan, P. Jayagopal, J.C. Babu, Wireless Sensor Networks Based on Multi-Criteria Clustering and Optimal Bio-Inspired Algorithm for Energy-Efficient Routing. Applied Sciences, 13(5), (2023) 2801.
<https://doi.org/10.3390/app13052801>
- [24] Alsarayreh, B.F. A Comparative Analysis of Swarm Intelligence Algorithms for Event Detection in Wireless Sensor Networks. Journal of Electrical Systems, 20(11), (2024).
<https://doi.org/10.52783/jes.7290>
- [25] A. Kumari, S. Malik, Energy-Efficient Data Aggregation in Wireless Sensor Networks using Neural Network-Based Prediction Models. Communications on Applied Nonlinear Analysis, 32(2s), (2025) 466-481.

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R. Chitra: Conceptualization, Methodology, Resources, Writing - Original Draft. R. Sudarmani: Methodology, Investigation, Software, Writing - Review & Editing. Both the authors have read and agreed to the published version of the manuscript.

Funding

The authors declare that no funds, grants or any other support were received during the preparation of this manuscript.

Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

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