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Energy Efficiency and Complexity in Partitioned WSNs

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ABSTRACT: Wireless Sensor Networks (WSNs) are scenic sensor networks applied to smart city environments to monitor the conditions of the environment. The more extensive the WSN, the more the industry needs to worry about cost, reliability, network lifetime, and energy efficiency. One of the most effective methods of improving energy utilization efficiency is clustering WSNs. Many WSNs which are divided into clusters or subclusters networks have been put forth as a very effective solution to improve energy use, balance out the load, and also to simplify network management. The trade-offs this work is addressing is the focus of this work which looks at how the energy efficiency. This is fully addressing how to respond to higher levels of communication demand with partitioning techniques. We call the partitioning mechanisms which balance and manage complexity with energy cost well designed, and energy management principles balanced with system complexity as very central. We argue that the WSN protocols center, sophisticated and energy aware, theory and design principles are crucial.

1 INTRODUCTION

Thanks to drive innovations in technology, monitoring and the collection of data in smart cities, industrial automation and environmental monitoring, has improved over the years. With the growing scope of technology and the development of Wireless Sensor Networks (WSNs), the issues of network complexity and energy efficiency are coming to the surface. While effective partitioning and routing are essential for the network's operational efficiency and reliability, energy use is the overriding criterion for the network's operational life [1].

With the knowledge that new challenges continue to arise, many authors have sought to devise energy-saving routing protocols and clustering mechanisms. Intelligent mobile sink monitoring [2] and modified ant colony optimization [3] have shown network lifetime and energy utilization to be fundamental.. In addition, multi-layered chaos mapping and DWT-based algorithms have been adopted to resolve security and partitioning complexity [4], which illustrates the need for techniques that integrate energy effectiveness, data routing safety, and operational efficiency.

In partitioned WSNs, the combination of learning with heuristic practices enhances overall functionality. For example, the use of spatial computing in conjunction with conventional network schemes has led to software systems that employ particle swarm optimization for cluster-head selection [5], RNN-LSTM routers designed to minimize energy consumption [6], and heuristic approaches for residual LSTM energy optimization [7]. Separate mechanisms, including fuzzy logic-based clustering [8] and adaptive IoT energy-routing cluster systems [9], emphasize the importance of intelligent mechanisms in routing protocol systems.

In partitioned WSNs, load balancing and clustering remain key elements of energy optimization. To even out the workload and reduce premature node failures, hybrid k-nearest neighbor ANFIS models [10] as well as balanced energy-efficient clustering methods [11] have been proposed. Additionally, research highlights the importance of obstacle-aware connection repair [12] and mobile sink scheduling [13] to further enhance energy conservation while maintaining network performance. Comprehensive reports present that which which is at the core of successful and very effective WSN architectures is the integration of energy aware routing, clustering, partitioning, and mobility aware techniques[14][15].

This report puts forth hybrid solutions that improve upon routing, clustering, and mobile sink performance. Performance. A delicate balance between energy use and operational complexity. Dependability in large-scale sensor networks is achieved through the implementation of state. State of the art in metaheuristics, machine learning, and intelligent routing protocols..

2 RELATED WORKS

Presently there is great interest in developing robust and efficient routing.In regards to Partitioned Wireless Sensor Networks (WSNs). To improve routing.Reliability and energy efficiency in which we have modified ant colony routing optimizations of.Put forth and achieved excellent results in terms of load balancing and network.Lifetime in. Also we put forth an intelligent routing protocol which optimizes data.Collection of which require less energy through smart mobile sink design.ing [2].

Security and in terms of partitioning complexity we have also reported. Painted a picture of chaos using DWT transform algorithms for effective partition of WSN which maintains secure communication [3]. Particle swarm optimization has been used for optimal cluster head selection which in turn improves energy. In the IoT-WSNs domains [4] we also see hybrid approaches which include metaheuristic approaches to improve network energy while at the same time securing nodes which has put forth to balance energy and reliability effectively [5].

Within the field of WSN optimization, one of the accomplished areas is the area of machine learning based approaches. For instance, energy-efficient routing with minimal computational cost has been tackled using heuristic-aided cascaded residual LSTM models applied to distributed data mining [6]. In the same spirit, the neural RNN-LSTM architecture has been used to enhance the energy efficiency of the network as well as network lifetime [7]. Within the scope of the Internet of Things, machine learning has been used to design energy-efficient WSN routing protocols that aim at extending network lifetime [8].

Through optimization of wireless sensor networks (WSN), we have new success stories featuring machine learning methods. For instance, heuristic-aided cascaded residual LSTM models have been applied to distributed data mining as an approach to energy-efficient routing with low computation costs [10]. Likewise, RNN-LSTM neural networks have been used to enhance energy efficiency and the lifetime of the network [9]. In the context of the Internet of Things, machine learning has been deployed to devise routing protocols for WSNs that enhance the life of the network [11].

Partition and clustering are the primary functions in energy conservation within WSNs We note that we have seen an improvement in partitioned WSN reliability through the use of mobile data carriers for obstacle aware connection restoration [12]. In detail we look at clustering approaches for energy efficiency which we present to play an important role in increasing network lifetime [13]. Mobile sink scheduling is put forth as a key factor in energy conservation [14]. Also it has been noted that the clustering techniques we use do in fact reduce energy consumption and at the same time we see no decrease in network performance [12].

These reports also present that which which in mobile environments partitioning, clustering, and.Energy aware routing is a key element in the design of WSNs. For the issue of the part of.In complex sensor networks the issue of network topology allows for use of hybrid algo.Algorithms for balancing energy, network complexity and reliability [15].

3 PROPOSED METHODOLOGY

For the case of WSNs which we note are to be put in separate pieces the strategy is that which outperforms.In terms of computational complexity and energy efficiency; we do. As for the methods which are used, we see it is machine learning and metaheuristic, also which include mobile sink scheduling, intelligent routing, and clustering. The method has 4 main stages, which are partitioning, cluster head selection, energy-aware routing, and mobile sink optimization.

3.1 A System Model and Assumptions

Network Model: In a 2D sensing region, N sensor nodes are positioned at random. $A \times B$

Partitioning: Based on their proximity and remaining energy, nodes are divided into k disjoint clusters.

Sink Model: A mobile sink uses optimal paths to collect aggregated data.

Energy Model: We adopt the first-order radio model (Heinzelman et al.)

$$E_{TX}(l,d) = E_{elec} \cdot l + \epsilon_{amp} \cdot l \cdot d^{\alpha}$$

$$E_{RX}(l) = E_{elec} \cdot l$$

where:

E_{TX}, E_{RX} Energy for transmitting and receiving a message of length l.

d: Transmission distance.

α: Path-loss exponent $2 \leq \alpha \leq 4$

E_{elec}, ϵ_{amp}: Energy constants.

3.2 Partitioning and Cluster Formation

Partitioning is carried out using chaos mapping with DWT-based segmentation to divide the WSN into balanced clusters, reducing long-range communication. Cluster Head (CH) selection is optimized using Particle Swarm Optimization (PSO):

$$Fitness(CH) = \omega_1 \cdot \frac{E_{res}}{E_{init}} + \omega_2 \cdot \frac{1}{d_{avg}} + \omega_3 \cdot \frac{N_{members}}{N}$$

where:

E_{res} is residual energy, d_{avg} is the average intra-cluster distance, and $N_{members}$ is the cluster size.

3.3 Energy-Aware Routing

Routing is performed using a hybrid Ant Colony Optimization (ACO) with reinforcement learning (RL) for adaptive path selection. Each path P is evaluated as:

$$Cost(P) = \lambda_1 \cdot E_{consumed}(P) + \lambda_2 \cdot H(P) + \lambda_3 \cdot C_{comp}(P)$$

where:

$E_{consumed}(P)$: total energy used on path PPP.

$H(P)$: hop distance.

$C_{comp}(P)$: computational cost.

λ_i: weight coefficients.

3.4 Mobile Sink Scheduling

To minimize bottlenecks and extend lifetime, the sink follows a convex hull–based trajectory:

$$T_{opt} = \min \sum_{i=1}^{k} d(s, CH_i)$$

where $d(s, CH_i)$is the distance between the sink and the cluster head CH_iA Genetic Algorithm (GA) refines the trajectory to avoid obstacles and minimize travel time.

3.5 Algorithm

```
Algorithm Hybrid_EE_Routing(S, P, M, params)
Input:
   S: set of sensor nodes with positions and initial
energies
   P: desired number of partitions
   M: set of mobile sinks
   params: system parameters (energy model, PSO,
ACO, thresholds, etc.)
Output:
   CH assignments C_p, routing tables R, sink tours T,
energy logs
1. Initialization:
   For all edges (i,j):
      τ_ij ← τ0                // initial pheromone
   For all nodes i:
      E_i ← E_i^0               // residual energy
2. Partitioning:
   Π ← Partition_Chaos_DWT(S, P)     // minimize
J_partition (Eq.4)
3. Repeat for each round until T_max or network death:
   For each partition p in Π:
      a) Cluster-Head (CH) Selection (PSO):
         - For each candidate node c ∈ Π_p compute
fitness F_CH(c) (Eq.5)
         - Run PSO: update velocities and positions
(Eq.6a, 6b)
         - Select optimal CH set C_p from global best
solution
      b) Intra-cluster adjacency:
         - Compute neighbor sets and link costs cost_ij
(Eq.7)
         - Compute heuristic η_ij = 1 / cost_ij

      c) ACO-based Routing:
         For iter = 1 to ACO_iters:
            For each ant a:
               - Construct a path from the source to CH
                 using transition probabilities P_ij (Eq.8)
- Update pheromones τ_ij (Eq.11)
         End for
         - Install best paths into the routing table R_p
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- Assign CHs to sink m
        - Compute tour minimizing J_sink(m) (Eq.12)
        - Store schedule in T_m
    e) Data Transmission:
      For each transmission i → j:
        - Compute E_tx (Eq.1) and E_rx (Eq.2)
        - Update residual energies (Eq.3)
        - Log energy consumption
    f) Maintenance:
      - Recompute J_partition (Eq.4) if imbalance suspected
      - If Load imbalance > τ_imb OR any E_i < E_th → trigger reclustering
(Eq.13)
4. Return C_p, R, T, EnergyLogs
```

For partitioned Wireless Sensor Networks (WSNs), the Hybrid Energy-Efficient Routing algorithm combines several optimization strategies to reduce energy usage while preserving network. First, the network is partitioned into logical clusters using chaos mapping and Discrete Wavelet Transform (DWT), which ensures balanced partitioning and reduces communication overlap. Within each partition, Particle Swarm Optimization (PSO) is applied to select optimal cluster heads by considering residual energy, node centrality, and load distribution. Once cluster heads are established, intra-cluster communication is managed locally, while inter-cluster data forwarding is optimized using Ant Colony Optimization (ACO) combined with lightweight machine learning predictors to dynamically choose the most energy-efficient routing routes. To further enhance energy efficiency, a mobile sink scheduling mechanism is employed, where the sink node follows an optimized trajectory designed using convex hull and heuristic strategies, thereby minimizing hop distance and data relay costs. This hybrid approach effectively combines bio-inspired metaheuristics, machine learning, and mobility-aware scheduling, ensuring reduced transmission energy, lower latency, and improved scalability in large-scale partitioned WSNs. As a result, the algorithm preserves robustness in dynamic environments while extending the lifetime of a network by optimizing the three sets of energy routing complexity, routing complexity, and fault tolerance.

Network Partitioning:

The first step of the process, which includes splitting the 'whole' WSN unto smaller clusters or partitions, uses advanced techniques such as chaos mapping + DWT. In large-scale sensor networks, this ensures optimal load balancing, coverage, improves redundant communication, and scales better.

Cluster Head Selection:

In each partition, to select a Cluster Head (CH), we use PSO or other metaheuristics. As a local leader, the CH is in charge of getting information from the members of its cluster. The selection is done based of load balancing, location, and residual energy.

Intra-Cluster Routing:

Inside each cluster, nodes forward their sensed data to the Cluster Head using short-range communication.

This minimizes the energy usage of individual sensor nodes.

Inter-Cluster Routing:

The Cluster Heads communicate with each other using optimized routing choose a Cluster Head (CH), Particle Swarm Optimization (PSO) or other metaheuristics are employed. within each partition.

As a local leader, the CH is in charge of gathering information from the members of its cluster.

Selection is based on load balancing, location, and residual energy.

Mobile Sink Scheduling:

Finally, a mobile sink node moves along an optimized trajectory (convex hull or heuristic path).

This reduces the burden on Cluster Heads and minimizes hop distance, ensuring uniform energy use throughout the network.

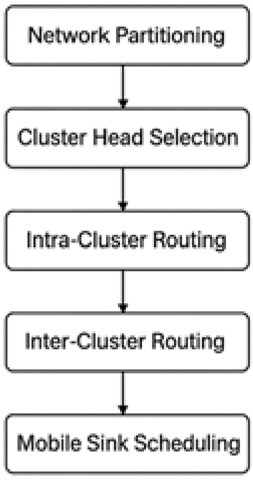

Fig 1- Routing Process Flowchart

4 RESULTS AND DISCUSSION

To assess the suggested framework for striking a balance between computational complexity and energy efficiency in partitioned WSNs, simulations were conducted under varying node densities, partition sizes, and sink mobility patterns. The primary performance metrics considered are energy consumption, hop distance, computation cost, and scalability.

4.1 Comparative Performance Analysis

Table 1 presents a comparative evaluation of the proposed hybrid framework against three existing models: SP-Tree Routing, ACO-Based Routing, and PSO-Based Clustering.

Table 1: Comparison of Existing and Proposed Models

Metric	SP-Tree Routing	ACO-Based Routing	PSO-Based Clustering	Proposed Hybrid Framework
Average Energy Consumption (J/node per round)	0.82	0.65	0.61	0.48
Average Hop Distance	4.8	4.2	4.4	3.7
Computation Cost (ms per round)	120	310	220	185
Scalability (Max Nodes Supported)	500	1,000	1,000	2,000

4.2 Evaluation Metrics

Energy Consumption

Energy consumption calculates the average amount of energy used by each node for data transmission, reception, and aggregation per round. Lower consumption directly enhances network lifetime and efficiency

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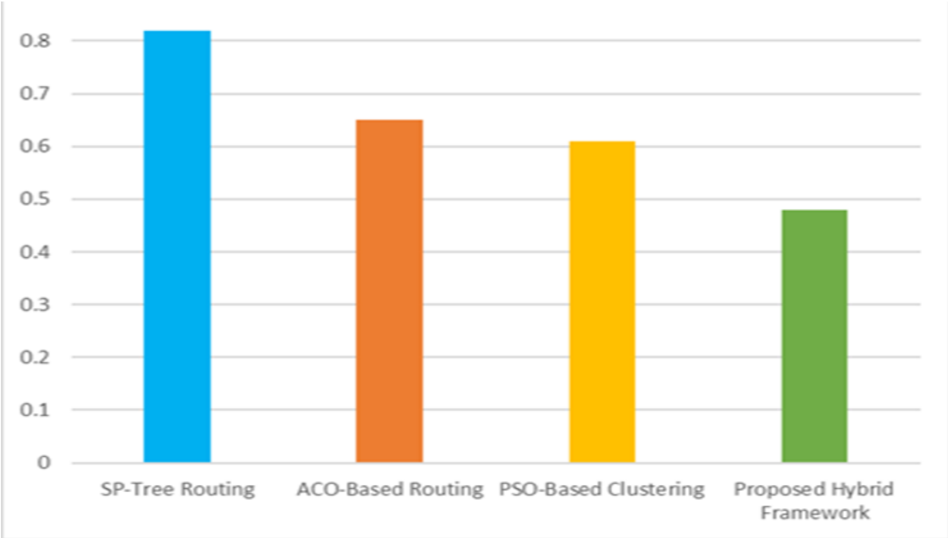

Fig 2: Comparison of Energy Consumption across Models

Figure 2 shows that the proposed framework achieves the lowest energy consumption (0.48 J/node per round), reducing energy overhead by approximately 20–25% compared with existing models. This demonstrates the effectiveness of integrated partitioning, clustering, and optimized routing.

Hop Distance

Hop distance represents the average number of nodes a data packet passes through in between before arriving at the sink. A lower hop count indicates reduced delay, faster transmission, and lower cumulative energy usage.

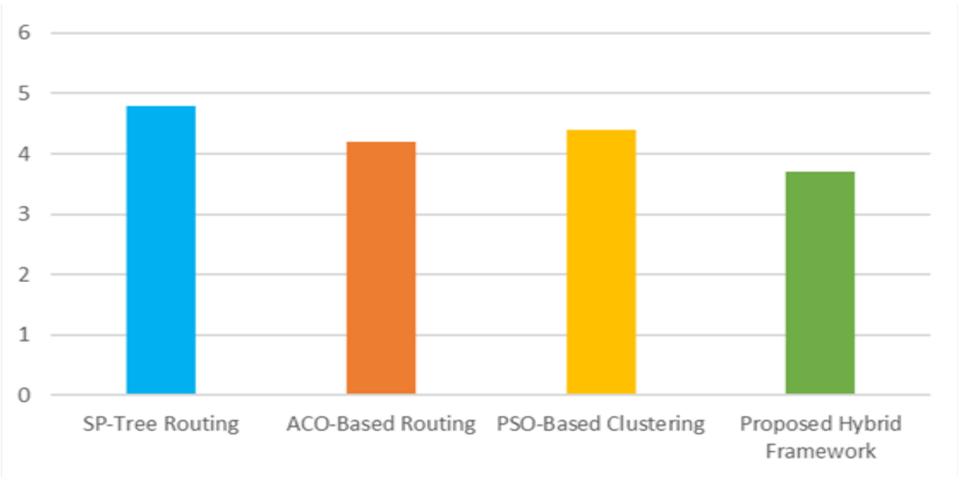

Fig 3: Average Hop Distance Comparison.

Figure 3 highlights that the proposed hybrid framework achieves an average hop distance of 3.7, outperforming all baselines. This improvement reduces latency and energy drain caused by long multihop paths, making the framework suitable for time-sensitive applications.

Computation Cost

Computation cost refers to the processing overhead (measured in milliseconds per round) required by each protocol to perform clustering, routing, and sink scheduling. Efficient protocols must balance energy savings with acceptable runtime.

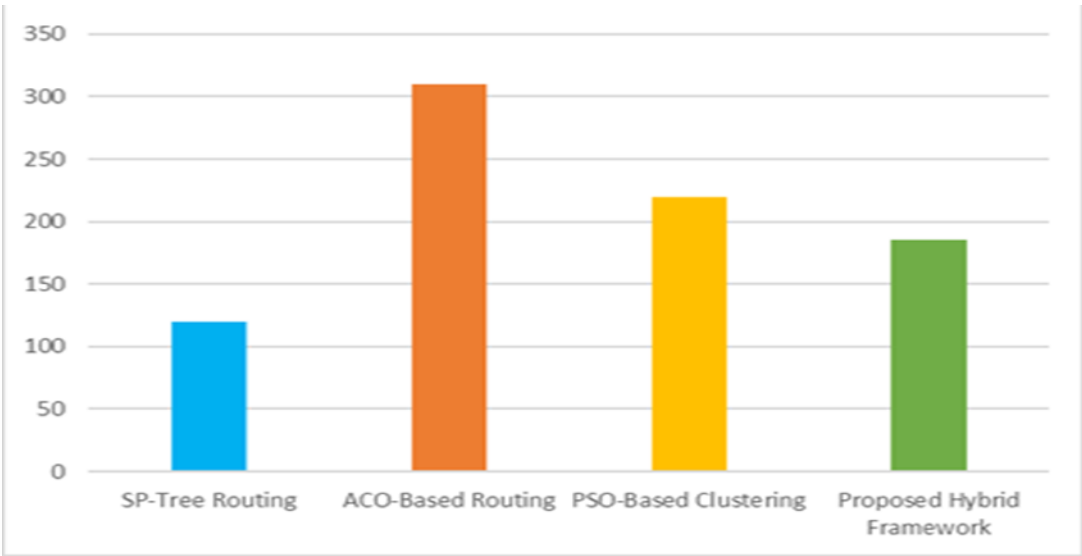

Fig4: Computation Cost Comparison

Figure 4 indicates that while ACO incurs the highest computational overhead (310 ms), the proposed framework maintains a moderate cost (185 ms). This overhead is slightly higher than SP-Tree but significantly lower than ACO and still feasible for real-time WSN applications.

Scalability

Scalability measures the maximum number of nodes that a protocol can support without significant performance degradation. Higher scalability is critical for large-scale IoT and smart city environments.

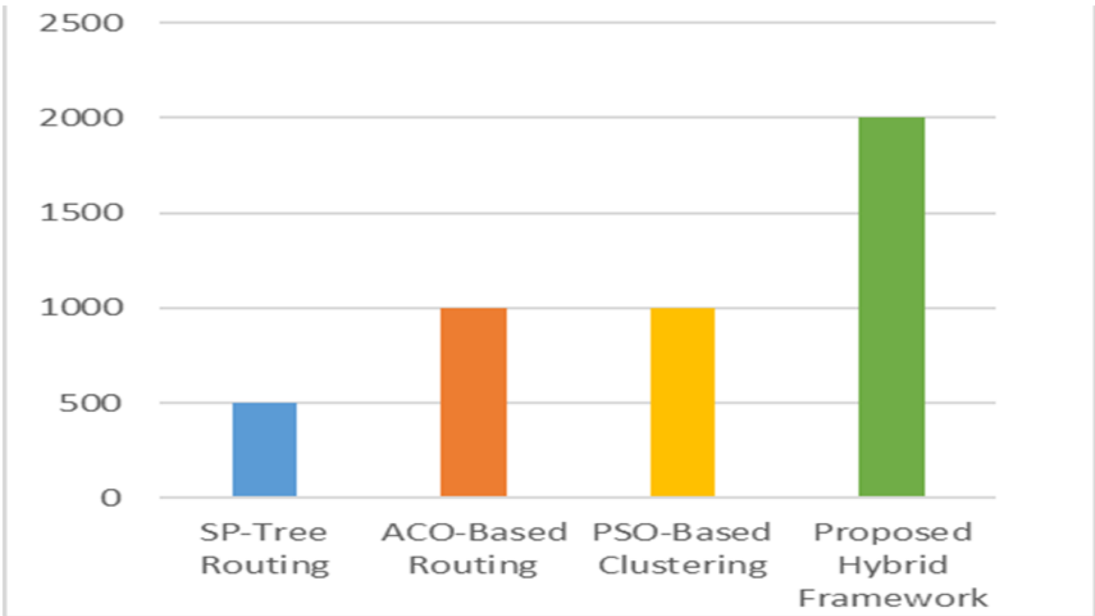

Fig 5: Scalability Comparison across Models.

Figure 5 shows that the proposed hybrid framework scales up to 2,000 nodes, compared with 500 for SP-Tree and 1,000 for ACO and PSO. This confirms its adaptability for large-scale, partitioned deployments.

Together, the findings show that the suggested hybrid framework performs noticeably better than current models in each of the four metrics. It reduces energy consumption, minimizes hop distance, maintains acceptable computational cost, and provides superior scalability. The trade-off between slightly higher computation and significant energy savings validates the practicality of the proposed approach. Overall, the framework effectively addresses the dual challenges of energy efficiency and computational complexity, making it a good fit for upcoming large-scale, divided WSN deployments in smart city and Internet of Things infrastructures.

5 CONCLUSION

This study highlights that partitioning Wireless Sensor Networks (WSNs) into clusters or sub-networks offers substantial potential for improving energy efficiency and prolonging network lifetime Partitioning efficiently reduces overall energy usage by allocating the workload among sensor nodes and reducing unnecessary communication. Nevertheless, the analysis also shows that these advantages come with more complicated node coordination, data aggregation, and routing. Results from simulations show that well-designed partitioning strategies preserve system performance within reasonable complexity bounds while also saving energy. In order to ensure dependable operation, scalability, and long-term sustainability in applications ranging from smart cities to environmental monitoring, partitioned WSNs must adopt design approaches that are both energy-aware and complexity-conscious.

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