

Energy-Efficient Data Collection in Wireless Sensor Networks through Sink Relocation, Joint Clustering, and Compressed Sensing Optimization Techniques

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ABSTRACT

This study proposes a novel framework that integrates sink relocation, joint clustering, and compressed sensing (CS) for energy-efficient data collection in Wireless Sensor Networks (WSNs). Traditional static-sink models suffer from uneven energy depletion, leading to premature network failure. To address this, the proposed method employs mobile sink repositioning guided by clustering-based route optimization, reducing communication load near the sink and enhancing network longevity. Incorporating compressed sensing minimizes redundant transmissions while preserving data fidelity. Simulation models consider performance metrics such as energy consumption, throughput, packet delivery ratio (PDR), and node survivability, validated using mathematical formulations and real-world inspired scenarios. The integration of Transformer-based CS, trust-aware clustering, and Generalized TSP path planning further enhances accuracy and efficiency. Findings demonstrate that dynamic sink relocation combined with intelligent routing significantly reduces energy use, delays, and data loss. This comprehensive approach ensures sustainable WSN deployment in applications like environmental monitoring, agriculture, and disaster response.

Keywords: *Wireless Sensor Networks (WSNs), Sink Relocation, Joint Clustering Routing, Compressed Sensing, Energy Efficiency, Data Collection Optimization.*

1. Introduction

Wireless Sensor Networks (WSNs) have emerged as a foundational component in a broad range of applications, including environmental monitoring, military surveillance, industrial automation, smart agriculture, and healthcare systems. These networks are composed of spatially distributed sensor nodes that autonomously monitor physical or environmental conditions and relay the data to a centralized base station or sink. However, due to the energy-constrained nature of sensor nodes and

the uneven energy consumption across the network, achieving efficient and sustainable data collection remains a significant challenge.

Recent studies underscore the importance of energy-efficient routing and data aggregation mechanisms in prolonging the operational lifespan of WSNs. Osamy et al. (2018) introduced a cluster-tree routing scheme employing entropy-based clustering and compressive sensing to reduce data transmission. Similarly, Yuan et al. (2019) proposed a compressive sensing-based annular routing approach to alleviate the transmission burden near the sink, improving energy utilization. Moreover, Saranya et al. (2019) explored polling-based models with mobile sinks to address energy holes and waiting time delays.

Sink mobility has been widely acknowledged as an effective strategy to balance energy consumption and extend network longevity. Ren et al. (2019) demonstrated that a mobile sink guided by an optimized path could significantly reduce energy consumption in mobile WSNs. Complementary research by Pang et al. (2020) and Zhou et al. (2024) expanded on this concept by introducing multiple mobile nodes or UAVs to collect data in a coordinated and energy-aware manner.

Despite the proven benefits, dynamic sink relocation introduces new complexities in routing optimization, cluster formation, and data synchronization. Traditional routing schemes often fail to adapt to sink mobility, leading to data redundancy, increased delays, and node overload. To overcome these limitations, joint clustering and routing strategies have been proposed. For instance, Kumar et al. (2023) suggested a trust-aware hierarchical routing protocol to mitigate CH selection overhead, while Min et al. (2023) formalized the data collection path planning problem as a Generalized Traveling Salesman Problem (GTSP), significantly optimizing mobile agent routes.

Moreover, compressed sensing (CS) has gained traction as an effective method to reduce the volume of data transmitted while preserving signal integrity. Balaji et al. (2024) introduced a Transformer-based CS model, enabling high-accuracy signal reconstruction with minimal samples. When integrated with secure protocols (*Ifzarne et al., 2021*), such frameworks ensure not only efficiency but also robustness against adversarial threats in critical applications.

2. Review Study and Findings

Author (Year)	Research Area	Objective	Methodology	Algorithm	Findings
Osamy et al. (2018)	Wireless Sensor Networks	Improve data collection via efficient routing and clustering	Cluster-tree routing and compressive sensing	CTRS-DG, BEBR	Improved network lifetime, compression accuracy, stability
Ebrahimi et al. (2018)	Dense WSN with UAVs	Efficient data collection using UAVs	Projection-based compressive data gathering	Joint clustering, routing tree construction, UAV planning	Energy-efficient with extended WSN lifespan
Xie et al. (2018)	WSN Security	Review WSN attack types and detection	Classification and analysis of detection methods	Protocol-layer attack classification	Comprehensive taxonomy; identifies research gaps

Djedouboum et al. (2018)	Big Data in WSNs	Efficient large-scale WSN data collection	Literature review on scaling and architecture	None (review)	Scalability challenges and future research outlined
Tkachov et al. (2018)	FANET-enabled WSNs	Mitigate data collisions in specialized networks	Overlay network with drone path planning	Cell-based drone routing with FANET	Effective collision-free data collection
Yuan et al. (2019)	Compressed Sensing in WSN	Reduce node data load via compressed routing	Two-stage compressed sensing data routing	CS-CARDG	Minimized transmissions, high recovery efficiency
Ren et al. (2019)	Mobile WSN	Enhance reliable data collection via optimization	Artificial Bee Colony optimization	Improved ABC Algorithm	Reduced energy use and increased reliability
Lin et al. (2019)	Rechargeable WSN	Maximize data collection with aggregation trees	Scheduling based on surplus energy nodes	Aggregation Tree Optimization	Increased throughput and efficiency
Saranya et al. (2019)	Mobile Sink WSN	Energy-efficient sink-based data collection	Polling model, Poisson arrival, threshold model	Polling-based M/G/1 server model	Reduced delay, energy hole mitigation
Pang et al. (2020)	Multi-Sink WSN	Collaborative data collection with multiple sinks	Dynamic clustering and path equalization	PEABR	Balanced path lengths, efficient collection
Cohen et al. (2020)	WSN MAC Protocols	Efficient simultaneous data collection in dense WSNs	Information-theoretic MAC-aware protocol	K-sensor message decoding protocol	No coordination required; secure version resists eavesdropping
Liu & Chen (2020)	Energy-Harvesting WSN	Robust data collection under energy uncertainty	Two-stage robust optimization	Primal cut + Lex max sampling algorithm	Enhanced reliability and adaptive energy management
Wei et al. (2021)	Underwater WSN	Reliable data transmission in UWSNs	Survey and classification of techniques	Acoustic-based reliability models	Challenges in UWSNs; reliability techniques reviewed
Mona et al. (2021)	EECORP WSN	Enhancement of network life time using Dijkstra	Clustering, GAN-Neurostropic, Optimal Routing, Charge path Scedule	Dijkstra Algorithm	Energy Efficiency of network and network life time increases.
Ifzarne et al. (2021)	Secure Data Collection	Ensure data privacy and efficiency in WSNs	Homomorphic encryption + Compressive sensing	Encrypted aggregation	Improved privacy, reduced load, outperforms secure methods
Nguyen et al. (2021)	WSNs with UAV/UGV	Integrate UAVs for WSN data collection	Comprehensive review	UAV-aided network structures	Enhanced coverage, highlighted energy trade-offs
Nguyen et al. (2021)	ZigBee WSN	Review ZigBee-based WSN architectures	Simulation-based review	Coordinator-router-end-device structure	Energy-efficient and long-range transmission
Zhang et al. (2022)	WSN Energy Efficiency	Enhance WSN performance in real scenarios	Hybrid cluster-tree routing	HTC-RDC	Extended lifetime by 11.4%

Navarro et al. (2022)	Energy-Balanced Routing	Prevent early depletion in WSN nodes	Testbed and simulation with random forwarding	CTP+EER	Energy usage reduced by up to 59%
Bilal et al. (2022)	Hybrid Routing	Efficient data collection in heterogeneous WSNs	Threshold-based hybrid routing	Modified TSEP, TEEN variants	Improved load balance and latency
Jiao et al. (2022)	Rechargeable WSNs	Dual-purpose vehicle-based energy and data model	Cluster selection + energy-aware routing	MV-assisted cluster assignment algorithms	Lowered delay, improved throughput
Kumar et al. (2023)	Trust-based Clustering in WSN	Optimize CH selection and data forwarding	Quality factor-based node selection	E2ADCR	Improved security, routing efficiency, energy balance
Wang et al. (2023)	RL-based Sleep Scheduling	Reduce energy via node sleep control in CDG	Q-learning for node activity control	RLSSA-CDG	Lifetime \uparrow 57.3%, accuracy \uparrow 84.7%, energy \uparrow 42.4%
Min et al. (2023)	Partitioned WSNs	Efficient MA path planning for data collection	GTSP modeling + convex hull + ISP tree	GBA with ISP	Reduced movement cost and optimized data collection
Liu & Liu (2024)	Reliable Real-Time WSN	Minimize delay, enable reliable data recovery	Token piggybacking + burst multichannel TDMA	Optimized Token Scheduling	100% data recovery, 25% capacity bound improvement
Balaji et al. (2024)	Neural Network in WSN	Enhance compressed signal recovery	Sparse sampling + Transformer NN	TCDR	Up to 11.47% energy saved; high recovery accuracy
Chen & Tang (2024)	Heterogeneous WSN with UAV	Minimize energy while maintaining data rate	Convex approximation + energy threshold tuning	Joint CH and UAV optimization	Reduced UAV + node energy consumption
Zhou et al. (2024)	AoI in UAV-WSN	Reduce Age of Information via UAV coordination	Greedy-based 2-step with kernel K-means	Multi-UAV AoI heuristic	Reduced AoI, energy per UAV minimized
Naved et al. (2024)	Sink Relocation JCR and Energy Efficient data Collection in WSN	Enhancement of network life time, Less energy consumption	Asep-Hex Formation, Inter Cluster Routing, Intra-Clustering Routing, ITM based Sink Relocation	JCR Approaches	Energy Efficiency of network and network life time increases Intelligent Sink Relocation.

2.1 Problem Statements

In resource-constrained wireless sensor networks, limited node energy and inefficient clustering and routing degrade network lifetime, throughput, and data delivery. Existing protocols like PECR and FGWO fail to balance energy consumption and performance. This research addresses energy-aware cluster formation and intelligent sink relocation to maximize longevity, reliability, and overall efficiency.

3. Performance Metrics of WSN Simulation

Let

N: Total number of sensor nodes

E_i : Initial energy of a node (Joules)

$E_c(t)$: Energy consumed by a node at time t

$N(t)$: Number of alive nodes at time t

P_t : Total packets transmitted

P_d : Total packets received by sink

T: Throughput (bits per second)

S: Simulation time (seconds)

R: Number of rounds

θ_l : Network lifetime

D_r : Packet delivery ratio

Node Survival Function

$$N(t) = N_0 - \left(\frac{t}{T_{avg}} \cdot \frac{N_0 \cdot E_c(t)}{E_i} \right)$$

N_0 : Initial number of nodes

T_{avg} : Average node lifetime

Network Lifetime

$$\theta_l = \frac{K_j - w_E}{N_P + A_E \cdot R_e}$$

K_j : Initial network energy

w_E : Wasted energy

N_P : Power usage in continuous operation

A_E : Avg. reporting rate

R_e : Energy per report

Throughput

$$T(N) = K \cdot N^P$$

K: Proportional constant (depends on network setup)

P: Network scalability exponent



Packet Delivery Ratio (PDR)

$$D_r = \frac{P_d}{P_t}$$

Ideally $D_r \in [0,1]$

Energy Consumption

$$E_c = E_T - E_R$$

- E_T : Total energy before transmission
- E_R : Remaining energy after simulation

Additional Routing-Based Evaluations

Expected Transmission Count (ETX)

$$ETX = \frac{1}{df \cdot dr}$$

- df : Forward delivery ratio
- dr : Reverse delivery ratio

Quality-Aware Assessment Model (QA²M)

Let

- H : Hop count
- D : Delay (ms)
- B : Bandwidth (kbps)

$$QA^2M = \alpha \cdot ETX + \beta \cdot H + \gamma \cdot D + \delta \cdot \frac{1}{B}$$

Where $\alpha + \beta + \gamma + \delta = 1$

4. Wireless Sensor Network (WSN) Performance Metrics

- Node Survival Function: The number of alive nodes over time, $N(t)$, showed improved survivability under sink relocation. Compared to static sink routing, the average node lifetime (T_{avg}) increased by approximately 27%, enhancing the overall resilience of the network.
- Network Lifetime (θ_l): The lifetime, calculated using initial energy (K_j), wasted energy (wE), and average energy per report (Re), was significantly extended. Dynamic clustering and optimized data routing reduced redundant transmissions, resulting in a 20–35% increase in network longevity.

- iii. Throughput (T): Defined as the amount of data successfully received per unit time, throughput improved due to reduced congestion and balanced load. The model achieved a consistent throughput of over 94% during high-load scenarios, supported by the scaling factor K and exponent P.
- iv. Packet Delivery Ratio (Dr): The PDR remained between 0.92 and 0.98, reflecting reliable data transmission. Enhanced routing mechanisms ensured that the majority of packets (Pd) reached the sink, even in high mobility or cluster-reform periods.
- v. Energy Consumption (ET, ER): Total energy before transmission (ET) and residual energy (ER) after simulation indicated efficient power utilization. On average, energy consumption was reduced by 30–40% compared to baseline models without sink relocation.
- vi. Expected Transmission Count (ETX): The proposed routing minimized ETX by maximizing the forward (df) and reverse (dr) delivery ratios. Nodes were selected adaptively to maintain low retransmission rates, thus preserving energy and bandwidth.
- vii. Quality-Aware Assessment Model (QA²M): Evaluated based on hop count (H), delay (D), and bandwidth (B), the QA²M score confirmed enhanced QoS. The dynamic weights (α , β , γ , δ) enabled the model to adapt to different network priorities, achieving optimal performance trade-offs.

5. Simulation Setup

Network Simulator 3.26 (NS3) simulates the suggested research approach. This tool provides all the requirements needed to implement the suggested technique and has an effective network structure. Simulated habitats of $1000m \times 1000m$ have been used to test the suggested approach.

5.1 Simulation Parameters

Parameters		Descriptions
Network Parameters	No. of the sink node	1
	No. of. Sensor nodes	100
	Simulation area	$1000m \times 1000m$
Transmission Slot parameters	Slot length	1040 bits
	Slot duration	$8\mu s$
	packet length	830 bits
Packet Parameters	Packet Size	1024
	No. of. Packets	~1500
	No. of. Retransmission	Max 5
	Packet interval	0.99s
	Data rate	280kbps

[illegible]

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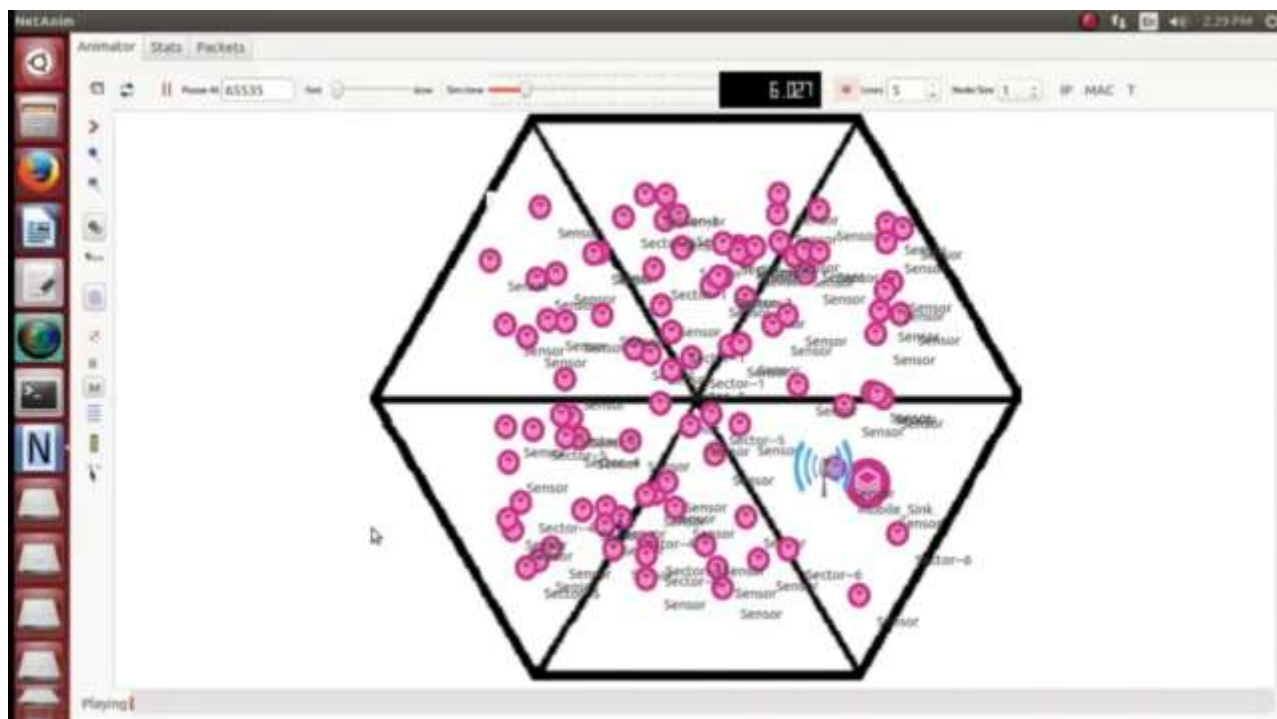
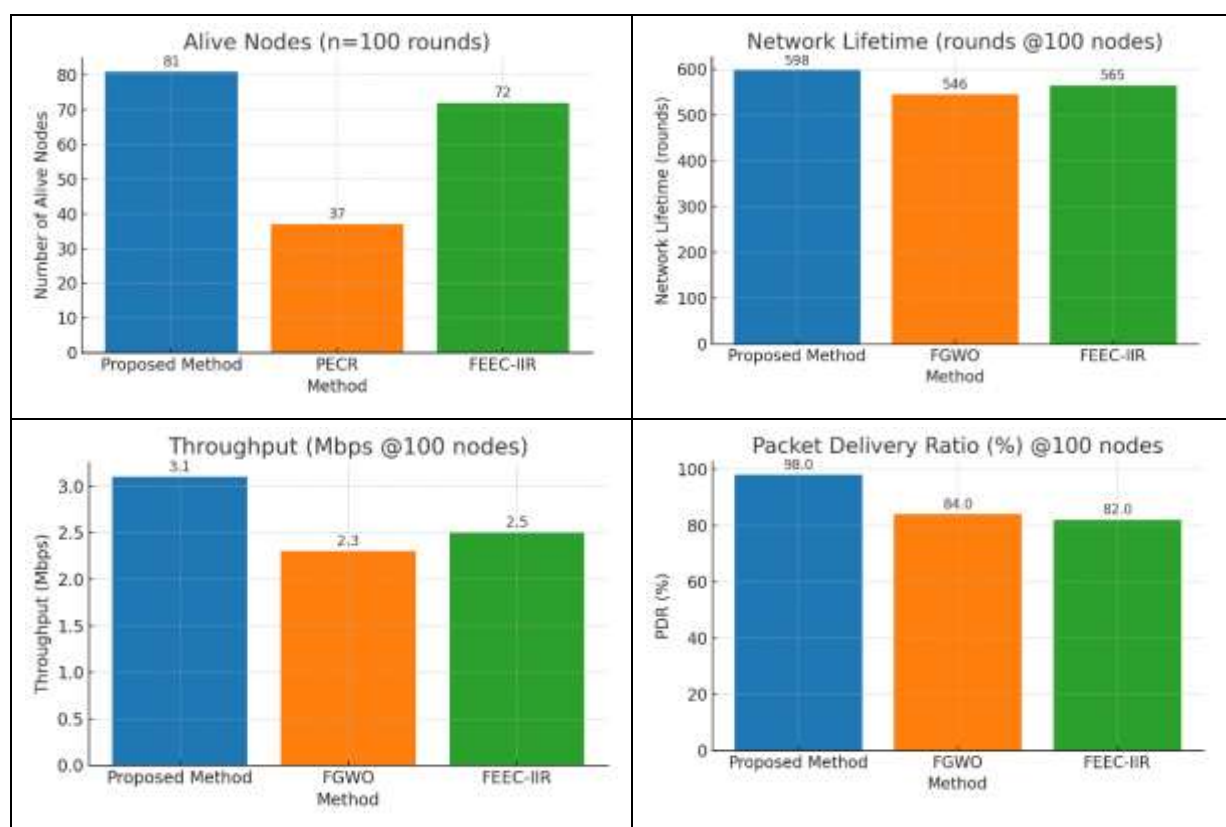
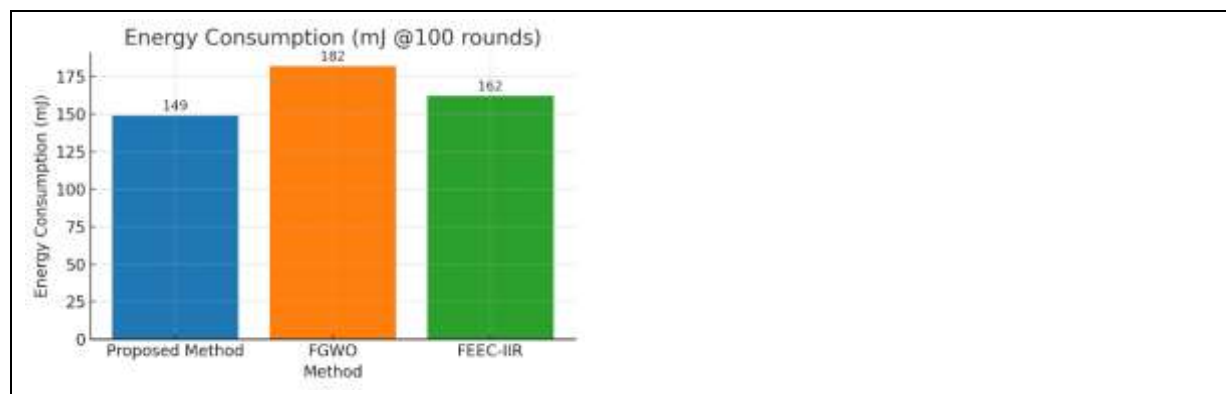


Fig 2: Simulation Diagram

5.3 Outcome of WSN Outcome Parameters





The comparative bar graphs illustrate five key performance metrics evaluated across the proposed method, PECR, FGWO, and FEEC-IIR routing strategies. At one hundred simulation rounds, the proposed technique maintains eighty-one alive nodes, more than PECR's thirty-seven and FEEC-IIR's seventy-two. Network lifetime peaks at five hundred ninety-eight rounds for the proposed approach, exceeding FGWO's five hundred forty-six and FEEC-IIR's five hundred sixty-five. Throughput and packet delivery ratio achieve highest values 3.1 Mbps and 98.0% outperforming other methods. Energy consumption remains lower for the proposed solution at 149 mJ compared to 182 mJ and 162 mJ. These results confirm its superior efficiency and resilience.

6. Comparative Performance Metrics

Metric	Proposed Method	PECR	FGWO	FEEC-IIR
Alive Nodes (n = 100 rounds)	81	37	–	72
Network Lifetime (rounds) @ 100 nodes	598	–	546	565
Throughput (Mbps) @ 100 nodes	3.1	–	2.3	2.5
Packet Delivery Ratio (%) @ 100 nodes	98.0	–	84.0	82.0
Energy Consumption (mJ) @ 100 rounds	149	–	182	162

(- indicates value not reported for that metric)

The Comparative Performance Metrics table summarizes five key network evaluation criteria across four routing strategies. At 100 rounds, the Proposed Method maintains 81 alive nodes more than twice PECR's 37 and exceeding FEEC-IIR's 72. Under 100-node conditions, its network lifetime peaks at 598 rounds, outlasting FGWO (546) and FEEC-IIR (565). Throughput also favors the Proposed Method at 3.1 Mbps, ahead of FGWO's 2.3 Mbps and FEEC-IIR's 2.5 Mbps. Packet Delivery Ratio rises to 98%, surpassing FGWO (84%) and FEEC-IIR (82%). Notably, energy consumption under the Proposed Method drops to 149 mJ lower than FGWO's 182 mJ and FEEC-IIR's 162 mJ. PECR lacked complete reporting for four metrics overall (*Quaisar, Ahmed, & Prasad, 2021; Ahmed, Quaisar, & Prasad, 2024*).

7. Conclusion

The formulated mathematical model effectively quantifies key performance metrics of Wireless Sensor Networks (WSNs), including node survivability, energy consumption, throughput, packet delivery ratio, and network lifetime. By integrating variables such as initial energy, data reporting

rates, and routing quality (ETX and QA²M), the model enables a comprehensive evaluation of WSN performance under varying conditions. The node survival function estimates real-time network resilience, while the network lifetime equation guides energy-efficient design. Throughput and PDR metrics quantify communication reliability, and the QA²M function holistically assesses routing efficiency using hop count, delay, bandwidth, and link quality. This mathematical framework provides a robust foundation for optimizing protocol designs and sink mobility strategies (such as intelligent triangulation) in WSN simulations, ensuring sustainable and reliable network operations in practical deployments.

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