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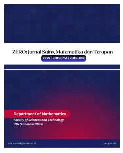

Performance Comparison of WSN Topologies in IoT-Based Water Quality Monitoring Systems

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ABSTRACT

This study, we quantify how WSN topology shapes QoS for IoT water-quality monitoring and derive deployment rules. Five topologies (Hybrid Star–Mesh, Cluster Tree, Full Mesh, Ring, ZigBee Star; 20 nodes) were simulated in NS-3 for 10 independent runs with random seeds. Our mathematical contribution is a compact QoS model set—latency LLL, packet-loss PlossP_{\text{loss}} Ploss, bandwidth usage UBU_BUB, and throughput TTT—used to compare topologies and compute relative/absolute improvements. Statistics report mean±SD with 95% confidence intervals from Student's t-distribution; pairwise Mann–Whitney tests with Benjamini–Hochberg FDR control (α=0.05) yield compact-letter displays; Cliff's δ quantifies effect sizes. Results: Hybrid Star–Mesh minimizes latency/loss while maximizing throughput; Ring is consistently inferior; Cluster Tree and ZigBee Star are mid-range; Full Mesh trades redundancy for delay and bandwidth. These models produce actionable guidance for aquaculture (real-time dissolved-oxygen) and urban drinking-water safety, and motivate multi-objective optimization (latency–throughput–energy) toward Pareto-optimal designs.

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1. INTRODUCTION

Water is an essential resource that supports public health, environmental sustainability, and economic development. Accelerated industrialization and urban growth have significantly degraded water quality, resulting in millions of fatalities annually due to water pollution-related diseases [1]. According to WHO data, more than 2 million deaths each year are linked to diseases caused chemical and physical pollutants as well as biological risks, jeopardize the potability of water and the equilibrium of ecosystems [2].

Traditional techniques for assessing water quality, which depend significantly on manual sampling and laboratory analysis, are insufficient for delivering prompt and extensive environmental evaluations. This method is time-consuming, expensive, and has limited reach, making it incapable of providing large-scale, real-time monitoring. This situation has prompted the emergence of alternative, more efficient and responsive technologies [3]. To address these constraints, Wireless Sensor Networks (WSNs) coupled with Internet of Things (IoT) frameworks have emerged as effective instruments for environmental monitoring, owing to their real-time capabilities, scalability, and reduced dependence on human involvement [4], [5].

The integration of Wireless Sensor Networks (WSN) with an Internet of Things (IoT) framework offers a scalable and automated solution for environmental monitoring. This technology enables continuous sensing and wireless data transmission, allowing for real-time monitoring of critical parameters such as pH, temperature, dissolved oxygen, and turbidity [6],[7],[8]. In the realm of water quality monitoring, Wireless Sensor Networks (WSNs) provide the ongoing assessment of essential parameters including temperature, pH, and total dissolved solids (TDS). These parameters are essential markers for assessing the health of aquatic ecosystems and for identifying early signs of contamination [9],[10]. Wireless Sensor Network (WSN) nodes generally incorporate sensors, microcontrollers, and wireless transceivers, all functioning on constrained power sources, necessitating energy-efficient system designs [11],[12].

Prior WSN research largely optimizes routing/MAC behavior without problematizing the structural choice of topology itself; protocol gains are then reported on top of whatever topology is assumed, which can confound causal attributions of QoS. For example, targets energy-reliable transmission in multi-sink WSNs, but the improvements arise from protocol-level redundancy and sink diversity under a specific connectivity pattern rather than from an explicit control of topology [13]. As a result, does not quantify whether its reliability–energy gains persist (or invert) across star/tree/mesh families, nor does it normalize against topology-dependent path lengths or duty cycles [13]. Likewise, analyzes delay and reliability in NS-3 but does so without a controlled, side-by-side comparison across canonical topologies; energy is not co-modeled, and application-level thresholds are not enforced [14]. Together, demonstrate the importance of reliability and delay modeling, yet they stop short of identifying when a given topology is preferable on mathematical or application grounds [13], [14].

In water-quality IoT, such omissions matter because acceptable service levels are domain-bound: aquaculture requires prompt detection of dissolved-oxygen drops to avoid mass mortality, whereas urban utilities need sub-second to sub-200 ms response windows for contamination alarms [15], [16]. A topology that minimizes loss under light load (e.g., star) may violate latency constraints under bursty events, while a topology that enhances redundancy (e.g., mesh) may inflate control overhead and energy per bit. Our study therefore isolates topology as the experimental variable—holding radio stack, traffic, node count, and range constant—and quantifies how Hybrid Star–Mesh, Full Mesh, Ring, Cluster Tree, and ZigBee Star reshape latency, loss, bandwidth use, and throughput under the same conditions. By mapping these outcomes to aquaculture and urban-utility thresholds, and by later adding energy metrics and lifetime markers, we extend the insights of and into prescriptive guidance on when each topology is mathematically and operationally preferable [13], [14].

In the context of public health, network delays above 200 ms can potentially hamper early warning systems for drinking water, preventing hazardous contamination from being promptly addressed. This compromises public safety and reduces the reliability of IoT-based monitoring systems [15], [16]. Therefore, a quantitative understanding of QoS performance is crucial.

This research contributes to systematic simulations using NS-3 on various WSN topologies (star, tree, mesh, clustered) in the context of IoT-based water quality monitoring. Evaluations are conducted on key QoS metrics—latency, packet loss, throughput, and bandwidth utilization—with varying node density and transmission range. The results of this study provide practical guidance for selecting the appropriate topology to maintain a balance between real-time reliability and energy efficiency [17],[18], [19],[20],[21].

Unlike previous research that focused on protocol improvements, this study's novelty lies in its topology-based comparative analysis specifically designed for IoT-based water quality monitoring. By linking network topology performance to QoS metrics, this study provides quantitative evidence and practical recommendations for environmental agencies, aquaculture operators, and urban water utilities in designing more effective and efficient WSNs [8], [13].

2. RESEARCH METHOD

This research utilizes a Wireless Sensor Network (WSN) architecture to monitor real-time water quality metrics such as pH, total dissolved solids (TDS), and temperature. The technique comprises four fundamental components: WSN architecture design, topology management strategy, Quality of Service (QoS) metric evaluation, and performance assessment across various node configurations. Figure 1 depicts the system architecture of the proposed IoT-based wireless sensor network (WSN) intended for real-time water quality monitoring. The architecture consists of three primary tiers: the sensor layer, the gateway layer, and the application layer [22].

2.1 Architecture of Wireless Sensor Networks

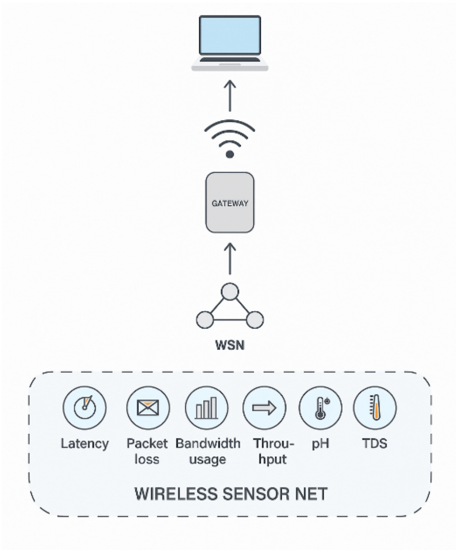

Figure 1. Schematic representation of the architecture

The WSN system consists of sensor nodes distributed across multiple clusters. Every node comprises a pH sensor, TDS sensor, temperature sensor, microcontroller unit, and wireless transmitter. Data gathered from the end nodes is transmitted to a local cluster coordinator, subsequently to a gateway, which ultimately conveys it to a base station. This hierarchical architecture facilitates energy-efficient routing and allows for scalability in extensive implementation [23],[24].

2.2 Strategy for Topology Management

A static cluster-based topology is employed to guarantee uninterrupted connectivity and reduce energy consumption. Each cluster is overseen by a coordinator node responsible for intra-cluster communication and data aggregation. The gateway oversees inter-cluster routing. This architecture reduces transmission cost and mitigates network segmentation, therefore improving stability [9],[11].

2.3 Quality of Service (QoS) Metrics

The network is assessed according to four key QoS parameters: latency, throughput, packet loss rate, and capacity utilization. Latency quantifies the temporal delay between data detection and its reception at the base station. Throughput measures the rate of successful transmissions. Packet loss signifies data reliability, while bandwidth usage denotes the efficacy of channel utilization [4], [25],[26], [27]. These measurements are essential for verifying real-time performance in vital environmental monitoring applications [28].

2.4 Mathematical QoS Metrics

To evaluate the system performance, four QoS indicators were modelled mathematically: latency (L), packet loss rate (P_{loss})_, bandwidth usage (U_B), and throughput (T).

Latency (ms):

$$L = \sum_{i=1}^{H} \left(\frac{P}{B} + \tau + Q \right) \tag{1}$$

Where,
P = Packet size (bits)
B = Bandwidth (bps)
τ = Propagation delay
Q = Queuing delay
This model follows latency evaluations in time-sensitive WSN deployments [9].

Packet Loss (%):

$$Ploss = 1 - (1 - p)^H \tag{2}$$

Where,
p = probability of packet loss per hop
H = number of hops
represents cumulative loss across hops, as observed in clustered IoT WSNs where stability varies by topology [29].

Bandwidth Usage (%):

$$UB = \frac{\sum_{i=1}^{N} Ri}{Rtotal}\, x\, 100\% \tag{3}$$

Where,
Ri = data rate on the second link-i
R_{total} = total bandwidth capacity
N = number of links
used to quantify link utilization, particularly under congestion [24].

Throughput (bps):

$$T = \frac{(1 - Ploss)\ \sum_{i=1}^{N} Ri}{\Delta t} \tag{4}$$

Where,
P_{loss} = packet loss rate
$\sum_{i=1}^{N} Ri$ = total data sent
Δt = measurement time interval
critical for real-time monitoring tasks [30].To evaluate the system performance, four QoS indicators were modelled mathematically: latency (L), packet loss rate (P_{loss})_, bandwidth usage (U_B), and throughput (T).

These models were parameterized for simulation and calibrated based on realistic hardware constraints (ZigBee/Wi-Fi hybrid at 250 kbps, 2.4 GHz, 100 m range) [10]. We configured each scenario with 20 sensor nodes to represent a single operational cell, consisting of one sink or cluster head and approximately 15–18 sensing or relay nodes. This configuration mirrors common water quality deployments where monitoring units are organized into clusters that can be tiled to achieve broader coverage. A 20-node set also exercises the light-to-moderate contention regime of IEEE 802.15.4 at 250 kbps, where QoS inflection points such as collisions, backoff expansions, and buffer overflows typically emerge.

Each experiment was executed for 300 seconds following a 30-second warm-up period. This duration yields 60–300 sampling cycles per node (depending on the interval), sufficient to capture steady-state behaviour and compute 95% confidence intervals across multiple seeds. Using this design, performance metrics—latency, packet loss, throughput, and bandwidth utilization—were averaged over multiple independent runs to ensure statistical significance. In practice, wide-area monitoring is achieved by composing multiple such 20-node clusters, making the results directly extensible to real-world implementations. Longer durations or larger node populations are only required for specialized analyses, such as tail-latency distributions or long-term energy lifetime studies, which lie outside the QoS focus of this work.

2.5 Experimental Configuration and Performance

Evaluation this study employed Network Simulator 3 (NS-3), a prevalent tool for simulating wireless communication networks, as its experimental framework [31], [32]. The network topology infrastructure for wireless sensor design is illustrated in Figure 2.

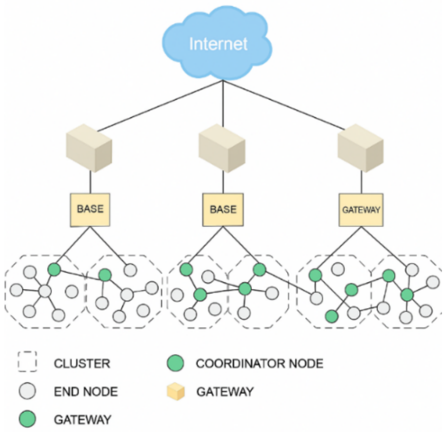

Figure 2. Network Topology Framework

The simulation model included five distinct wireless sensor networks (WSNs). The topology possibilities each comprise 20 sensor nodes distributed unevenly among various clusters. The deployment area was conceptualized as a 10 km² virtual environment simulating a diverse landscape for water quality monitoring [29]. Node placement was randomized inside each cluster in accordance with the parameters of each topological design. To ensure statistical robustness, each topology configuration (star, tree, mesh, clustered, and hybrid) was executed 10 independent times using different random seeds for node placement, traffic generation, and channel error models. For every run, the simulation lasted 300 seconds after a 30-second warm-up period.

The raw QoS metrics (latency, packet loss, throughput, and bandwidth utilization) were extracted for each run and then averaged across all repetitions. To characterize variability, we computed 95% confidence intervals (CI) around the mean values using Student's *t*-distribution, since the number of replicates was finite and below 30. In plots, the average values are presented as line curves, while the CI is represented by error bars or shaded bands.

This replication strategy provides statistical significance while balancing simulation runtime with coverage of different parameter settings (node density, buffer size, and traffic interval). By averaging across multiple seeds, the results reflect general trends in QoS behaviour, rather than artifacts from a single randomized run.

Each sensor node was configured to broadcast environmental data (pH, temperature, and TDS readings) at predetermined intervals, emulating real-time monitoring conditions. To realistically represent heterogeneous IoT architectures, we employed a dual-radio model:

ZigBee (IEEE 802.15.4) for intra-cluster communication among end nodes and cluster heads, leveraging its low-power consumption, low data rate (250 kbps), and short-range suitability (≤100 m per hop). Wi-Fi (IEEE 802.11) for gateway-to-base station communication, leveraging its higher throughput and longer-range backhaul capability. This design does not imply simultaneous dual-stack operation on each node. Instead, ZigBee modules were active on end devices and cluster heads, while Wi-Fi modules were enabled only at gateways to transmit aggregated traffic to base stations and subsequently to the Internet [33], [16],[34]. This hybrid configuration reflects real-world deployments where energy-efficient sensing is balanced with high-capacity data forwarding. Essential network configurations comprised a 2.4 GHz transmission frequency, a data rate of 250 kbps, and a maximum transmission range of 100 meters per hop [35], [36].

Performance was assessed using four principal QoS metrics: latency (average end-to-end delay in milliseconds), packet loss (percentage of lost packets during transmission), bandwidth utilization (percentage of total available bandwidth employed), and throughput (bits per second of successfully transmitted data). The gathered metrics were averaged across numerous simulation iterations to guarantee statistical consistency. These findings constitute the basis for the comparative analysis detailed in the subsequent section.

2.6 Routing Configuration

Routing configuration in Wireless Sensor Networks (WSNs) significantly influences the Quality of Service (QoS), especially in time-critical Internet of Things (IoT) applications such as water quality monitoring. In this study, the NS-3 RPL (Routing Protocol for Low-Power and Lossy Networks) implementation was used as the baseline routing protocol, since RPL is the de facto standard for constrained, multi-hop IoT deployments [2]. The baseline protocol was extended with customized modules to incorporate queue management techniques, including Random Early Detection (RED) and dynamic buffer adaptation, in order to mitigate congestion and reduce end-to-end latency[37],[38],[39],[40]. Adaptive retransmission mechanisms were also introduced, allowing nodes to intelligently adjust retry thresholds based on historical success rates and current energy availability, thereby minimizing packet loss and ensuring energy-aware delivery [9],[41],[17],[24],[42],[43]. These mechanisms are critical for real-time data acquisition, where transmission reliability and delay sensitivity are primary concerns.

Routing decisions were determined by a hybrid cost function that included parameters like residual energy, hop count, link quality indicator (LQI), and latency. The cost function included parameters such as residual energy, hop count, link quality indicator (LQI), and latency. The routing protocol could adapt to fluctuating network dynamics, thereby enhancing both stability and throughput [44],[18]. A predictive fallback routing mechanism was also implemented as a custom extension, utilizing link-quality forecasting and signal-to-noise ratio (SNR) trend analysis to facilitate pre-emptive rerouting prior to link loss [45] ,[30],[36]. Cross-layer optimization was employed to improve routing resilience, utilizing MAC-layer congestion signals and physical-layer interference assessments to guide real-time routing choices [15],[46].

Furthermore, cross-layer optimization was employed to improve routing resilience, incorporating MAC-layer congestion signals and physical-layer interference assessments to guide real-time routing choices [16]. In summary, the routing configuration can be described as a customized RPL variant: it leverages the existing NS-3 routing stack for fundamental forwarding operations, while introducing QoS-driven extensions and cross-layer feedback mechanisms tailored to water quality monitoring applications. Recent studies demonstrate that such cross-layer and QoS-driven routing strategies surpass traditional models in jitter reduction, fairness, and energy equilibrium inside clustered WSNs [8],[19].

3. RESULT AND ANALYSIS

We evaluated five wireless sensor network (WSN) topologies under NS-3 simulation—Hybrid Star–Mesh, Cluster Tree, Full Mesh, Ring, and ZigBee Star—using four quality-of-service (QoS) metrics: latency, packet loss, bandwidth usage, and throughput. Each scenario reflects realistic variations in cluster count and node distribution (20 nodes total), capturing the trade-offs between routing redundancy, gateway contention, and multi-hop efficiency. unevenly allocated among the clusters to replicate monitoring conditions over diverse coverage areas.

Scenario 1 employed a hybrid star-mesh topology over three clusters with a node distribution of 5, 7, and 8. This topology utilizes the benefits of mesh for routing dependability and star for energy efficiency, so attaining a balance between stability and communication performance.

Scenario 2 employed a full mesh architecture across four clusters (4-6-5-5 nodes), facilitating direct communication among nodes. This architecture offers extensive connectivity but also has considerable bandwidth consumption risks.

Scenario 3 had two clusters with distributions of 12 and 8 nodes, respectively, employing a ring architecture that depends on sequential pathways for data packet transmission. This configuration reduces the quantity of active pathways while heightening the likelihood of cumulative delays in periods of elevated traffic.

Scenario 4 employs a cluster tree methodology featuring five diminutive clusters (3-4-5-3-5 nodes) interconnected through multi-hop communication. This architecture emphasizes adaptive routing efficiency and alleviates the load on the central node, however necessitates precise synchronization among clusters.

Scenario 5 employs a ZigBee star topology featuring three clusters (6-8-6 nodes), in which each node connects directly with the central gateway. This structure, albeit simpler and more energy-efficient, tends to incur delays when the data load escalates concurrently.

Table 1 displays summaries scenario-level performance as mean ± SD with 95% bootstrap confidence intervals (CIs). The Hybrid Star–Mesh shows the lowest latency and loss with the highest throughput, whereas Ring is consistently worst; Cluster Tree and ZigBee Star fall in the middle, reflecting their respective balance between load distribution and gateway simplicity. These findings suggest that hybrid designs are optimal for balancing reliability, energy efficiency, and responsiveness, whereas tree and star topologies may be suitable for moderate-scale deployments, and mesh or ring structures are less effective under the evaluated conditions.

Table 1. Scenario-wise QoS (mean ± SD [95% CI])

Scenario	Topology	n	Latency (ms) — mean±SD [95% CI]	Packet Loss (%) — mean±SD [95% CI]	Bandwidth Usage (%) — mean±SD [95% CI]	Throughput (bps) — mean±SD [95% CI]
1	Hybrid Star–Mesh	20	67.56 ± 2.35 [66.17, 68.93]	2.10 ± 0.05 [2.07, 2.13]	60.86 ± 1.76 [59.88, 61.87]	404.25 ± 16.69 [394.98, 415.07]
2	Cluster Tree	20	78.40 ± 1.87 [77.28, 79.41]	2.97 ± 0.10 [2.91, 3.02]	58.72 ± 1.68 [57.73, 59.69]	381.13 ± 14.41 [373.83, 390.02]
3	Full Mesh	20	93.84 ± 2.69 [92.21, 95.42]	4.22 ± 0.08 [4.17, 4.26]	75.44 ± 1.74 [74.51, 76.49]	361.58 ± 10.36 [355.10, 367.73]
4	Ring	20	106.73 ± 2.27 [105.46, 108.07]	5.88 ± 0.16 [5.79, 5.97]	49.85 ± 1.49 [48.94, 50.73]	332.62 ± 11.73 [325.89, 339.13]
5	ZigBee Star	20	84.46 ± 2.38 [83.06, 85.81]	3.72 ± 0.11 [3.65, 3.78]	54.37 ± 1.98 [53.26, 55.57]	373.58 ± 11.04 [367.23, 379.77]

In Table 2, we assessed statistical significance with Mann–Whitney pairwise tests and Benjamini–Hochberg (BH) correction ($\alpha = 0.05$), reporting compact letter displays (CLD) per metric; scenarios sharing a letter are not significantly different. Practical significance is quantified with Cliff's δ versus the worst-performing scenario.

Table 2. Per-metric comparison with significance groups and effect sizes

Metric	Scenario	Topology	n	mean±SD [95%CI]	Improvement vs Worst (%)	Cliff's δ vs Worst	Sig. Group (BH 0.05)
Latency (ms)	1	Hybrid Star–Mesh	10	67.56 ± 2.35 [66.17, 68.93]	36.7	-1.000	a
Latency (ms)	2	Cluster Tree	10	78.40 ± 1.87 [77.28, 79.41]	26.5	-1.000	b
Latency (ms)	3	Full Mesh	10	93.84 ± 2.69 [92.21, 95.42]	12.1	-1.000	c
Latency (ms)	4	Ring	10	106.73 ± 2.27 [105.46, 108.07]	0.0	0.000	d
Latency (ms)	5	ZigBee Star	10	84.46 ± 2.38 [83.06, 85.81]	20.9	-1.000	e
Packet Loss (%)	1	Hybrid Star–Mesh	10	2.10 ± 0.05 [2.07, 2.13]	64.3	-1.000	a
Packet Loss (%)	2	Cluster Tree	10	2.97 ± 0.10 [2.91, 3.02]	49.5	-1.000	b
Packet Loss (%)	3	Full Mesh	10	4.22 ± 0.08 [4.17, 4.26]	28.3	-1.000	c
Packet Loss (%)	4	Ring	10	5.88 ± 0.16 [5.79, 5.97]	0.0	0.000	d
Packet Loss (%)	5	ZigBee Star	10	3.72 ± 0.11 [3.65, 3.78]	36.8	-1.000	e
Bandwidth Usage (%)	1	Hybrid Star–Mesh	10	60.86 ± 1.76 [59.88, 61.87]	22.1	1.000	a
Bandwidth Usage (%)	2	Cluster Tree	10	58.72 ± 1.68 [57.73, 59.69]	17.8	1.000	b
Bandwidth Usage (%)	3	Full Mesh	10	75.44 ± 1.74 [74.51, 76.49]	51.3	1.000	c
Bandwidth Usage (%)	4	Ring	10	49.85 ± 1.49 [48.94, 50.73]	0.0	0.000	d
Bandwidth Usage (%)	5	ZigBee Star	10	54.37 ± 1.98 [53.26, 55.57]	9.1	0.960	e
Throughput (bps)	1	Hybrid Star–Mesh	10	404.25 ± 16.69 [394.98, 415.07]	21.5	1.000	a
Throughput (bps)	2	Cluster Tree	10	381.13 ± 14.41 [373.83, 390.02]	14.6	1.000	b
Throughput (bps)	3	Full Mesh	10	361.58 ± 10.36 [355.10, 367.73]	8.7	0.940	c
Throughput (bps)	4	Ring	10	332.62 ± 11.73 [325.89, 339.13]	0.0	0.000	d
Throughput (bps)	5	ZigBee Star	10	373.58 ± 11.04 [367.23, 379.77]	12.3	1.000	b

To contextualize magnitudes, Table 3 reports relative improvements versus the worst-case baseline for each metric—reductions for lower-is-better metrics (latency, packet loss, bandwidth) and increases for higher-is-better (throughput)—alongside absolute differences (Δ) in native units.

Table 3. Relative Performance Improvements (vs worst-case baselines)

Scenario	Topology	Latency — Relative Reduction vs Worst (%)	Δ Latency (ms)	Packet Loss — Relative Reduction vs Worst (%)	Δ Packet Loss (pp)	Throughput — Relative Increase vs Worst (%)	Δ Throughput (bps)	Bandwidth Usage — Relative Reduction vs Worst (%)	Δ Bandwidth Usage (pp)
1	Hybrid Star–Mesh	36.7	39.0	64.3	3.8	21.5	72.0	19.3	14.6
2	Cluster Tree	26.5	28.0	49.5	2.9	14.6	49.0	22.2	16.7
3	Full Mesh	12.1	13.0	28.3	1.7	8.7	29.0	0.0	0.0
4	Ring	0.0	0.0	0.0	0.0	0.0	0.0	33.9	25.6
5	ZigBee Star	20.9	22.0	36.8	2.2	12.3	41.0	27.9	21.1

Clarification: for lower-is-better metrics, Relative Reduction vs Worst (%) = (Worst − Scenario)/Worst × 100; for throughput, Relative Increase vs Worst (%) = (Scenario − Worst)/Worst × 100. 'pp' = percentage points.

Subsequent research should corroborate these findings through practical implementations and investigate topology-aware, energy-adaptive routing algorithms to guarantee the sustainability of Quality of Service (QoS). Moreover, scalability assessments involving more than 50 diverse nodes must be performed to evaluate performance consistency in extensive IoT monitoring contexts.

Figure 3 overlays the four metrics across scenarios with 95% CIs and BH-adjusted significance letters. The hybrid design dominates latency/loss/throughput without excessive bandwidth usage, whereas Ring remains worst across metrics; Full Mesh trades higher bandwidth for higher delay and loss, and Cluster Tree/ZigBee Star offer mid-range profiles. The depicted metrics encompass delay, packet loss, bandwidth utilization, and throughput. Scenario 1 (Star-Mesh Hybrid) demonstrates the minimal latency and packet loss, along with the most throughput. While the Star-Mesh Hybrid topology demonstrated the strongest QoS performance, with minimal latency, low packet loss, and the highest throughput (410 bps), this advantage comes with inherent trade-offs. The hybrid design achieves reliability by leveraging mesh connectivity for redundancy and fault tolerance, while maintaining energy efficiency through star-based clusters. However, this structure also increases routing complexity, as the protocol must dynamically select between multiple paths while balancing hop count, link quality, and residual energy. Such complexity can elevate control overhead and require more sophisticated coordination at cluster heads, potentially impacting scalability in very large deployments. In contrast, simpler structures like the ZigBee Star reduce routing complexity but sacrifice resilience, while Cluster Tree architectures balance load but introduce synchronization demands. These findings suggest that hybrid topologies are optimal when throughput and reliability are critical, though they require more careful routing management and may incur higher processing and signaling costs. whereas Scenario 3 (Ring) reveals the least advantageous performance across all measures.

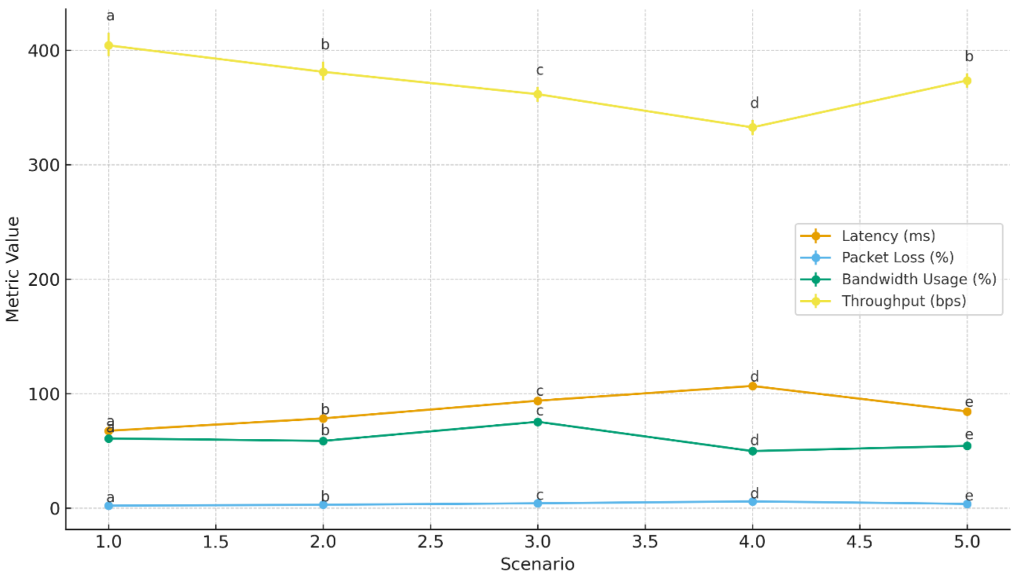

Figure 3. QoS Metrics with 95% CI and Significance Letters

Values are aggregated over replications (n) per scenario. We report mean ± SD and 95% bootstrap CIs; significance is evaluated via pairwise Mann–Whitney tests with BH correction, with compact letter displays per metric. Effect sizes use Cliff's δ relative to the worst-performing scenario ($|\delta|$ thresholds: negligible < 0.147, small < 0.33, medium < 0.474, large ≥ 0.474). QoS metrics across five WSN topologies using 95% bootstrap confidence intervals and BH-adjusted Mann–Whitney compact letter groups. The Star–Mesh Hybrid consistently dominates—lower latency and packet loss alongside the highest throughput—while maintaining moderate bandwidth usage. Full Mesh exhibits high bandwidth utilization at the expense of higher delay and loss; Cluster Tree yields a balanced mid-range profile. ZigBee Star performs acceptably but is gateway-limited, and Ring is consistently worst across metrics. Letters that differ indicate statistically significant differences at $\alpha = 0.05$; shared letters denote no detectable difference under the non-parametric testing.

4. CONCLUSION

Across five WSN topologies evaluated under controlled NS-3 scenarios, the Hybrid Star–Mesh consistently delivered the most favorable QoS profile (low latency and loss with the highest throughput), while Ring was uniformly inferior; Cluster Tree and ZigBee Star offered mid-range trade-offs and Full Mesh exchanged redundancy for higher delay and loss. These findings, however, arise under important constraints: a fixed network size (20 nodes) and prespecified cluster partitions; simulation-only conditions without hardware variability or channel impairments; and statistics that summarize replications but do not incorporate between-deployment variance (e.g., hierarchical/mixed-effects modeling) or parameter uncertainty propagation. Consequently, external validity and uncertainty quantification remain conservative.

From a decision-analytic standpoint, the Hybrid Star–Mesh is recommended when the design objective is to minimize latency and packet loss subject to a minimum throughput constraint (throughput ≥ T_{min}) and an energy budget per delivered packet ($E_{pkt} \le E_{max}$); this is typical for safety-critical alarms (e.g., drinking-water events). Cluster Tree is preferable when coverage requires multi-hop connectivity with moderate traffic and tight energy budgets—i.e., when maintaining E_{pkt} is prioritized over marginal gains in latency. ZigBee Star is suitable for low-density, periodic sensing with lax throughput demands (T_{min} modest) and strict duty-cycling. Full Mesh becomes optimal only when path redundancy and fault tolerance dominate and bandwidth utilization constraints are loose. Ring is rarely optimal except under deterministic, low-load pipelines where minimal control overhead is desired and reliability risks are acceptable.

Future work should cast topology selection and parameter tuning as a multi-objective optimization problem over the latency–throughput–energy surface. We suggest evolutionary approaches (e.g., NSGA-II/MOEA-D) to learn Pareto-optimal sets $\{\tau, \theta\}$ of topology τ and routing/scheduling parameters θ, jointly minimizing latency and loss while maximizing throughput and energy lifetime. This should be complemented by (i) variance-aware modeling (hierarchical/Bayesian analyses that partition run-to-run, topology, and environment effects), (ii) scaling studies beyond 50–100 nodes with heterogeneous traffic, and (iii) hardware-in-the-loop experiments to validate the Pareto front under real interference and duty-cycle constraints.

In summary, this research highlights that QoS-driven topology selection plays a decisive role in designing scalable, energy-efficient, and reliable IoT-based WSNs for real-time water quality monitoring, providing both immediate insights and a foundation for future optimization-driven methodologies.

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